2014-12

Identifying factors that predict promotion time to E-4 and re-enlistment eligibility for U.S. Marine Corps Field Radio Operators

Wathen, William G.

Monterey, California: Naval Postgraduate School

NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

IDENTIFYING FACTORS THAT PREDICT PROMOTION TIME TO E-4 AND RE-ENLISTMENT ELIGIBILITY FOR U.S. MARINE CORPS FIELD RADIO OPERATORS

by

William G. Wathen

December 2014

Thesis Advisor: Robert A. Koyak
Second Reader: Chad W. Seagren

THIS PAGE INTENTIONALLY LEFT BLANK

REPORT DOCUMENTATION PAGE			*Form Approved OMB No. 0704-0188*
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington DC 20503.			
1. AGENCY USE ONLY *(Leave blank)*	**2. REPORT DATE** December 2014	**3. REPORT TYPE AND DATES COVERED** Master's Thesis	
4. TITLE AND SUBTITLE IDENTIFYING FACTORS THAT PREDICT PROMOTION TIME TO E-4 AND RE-ENLISTMENT ELIGIBILITY FOR U.S. MARINE CORPS FIELD RADIO OPERATORS			**5. FUNDING NUMBERS**
6. AUTHOR(S) William G. Wathen			
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000			**8. PERFORMING ORGANIZATION REPORT NUMBER**
9. SPONSORING /MONITORING AGENCY NAME(S) AND ADDRESS(ES)			**10. SPONSORING/MONITORING AGENCY REPORT NUMBER**
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government. IRB Protocol number ____NPS.2014.0071-IR-EP5-A____.			
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release; distribution is unlimited			**12b. DISTRIBUTION CODE** A

13. ABSTRACT (maximum 200 words)

We develop statistical models to identify the most influential entry-level attributes of a Marine recruit to predict two performance measures: the Computed Tier Score and the time to achieve the rank of Corporal (E-4) in the 0621 Field Radio Operator Military Occupational Specialty (MOS). We use data collected from 2007 through 2014, on more than 1,100 Marines in the 0621 MOS to construct multivariate linear regression models to estimate Marines' Computed Tier Score and time to achieve E-4 based on their individual personal and professional attributes.

We find statistically significant relationships to exist between the entry-level attributes of a Marine recruit and the performance measures. The most influential predictor variables include the run time on the USMC Initial Skills Test (IST), number of crunches on the IST, rifle score, the Armed Services Vocational Aptitude Battery (ASVAB) General Technical (GT) score, ASVAB Clerical (CL) score, ASVAB General Science (GS) score, ASVAB Mathematics Knowledge (MK) score, ASVAB Paragraph Comprehension (PC) score, weight, and whether a Marine receives a weight waiver upon entrance into service. We recommend that new job performance measures be created for each high-density MOS in order to conduct further testing for MOS suitability.

14. SUBJECT TERMS career assignment, mos assignment, linear regression			**15. NUMBER OF PAGES** 77
			16. PRICE CODE
17. SECURITY CLASSIFICATION OF REPORT Unclassified	**18. SECURITY CLASSIFICATION OF THIS PAGE** Unclassified	**19. SECURITY CLASSIFICATION OF ABSTRACT** Unclassified	**20. LIMITATION OF ABSTRACT** UU

NSN 7540-01-280-5500 Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. 239-18

THIS PAGE INTENTIONALLY LEFT BLANK

IDENTIFYING FACTORS THAT PREDICT PROMOTION TIME TO E-4 AND RE-ENLISTMENT ELIGIBILITY FOR U.S. MARINE CORPS FIELD RADIO OPERATORS

William G. Wathen
Captain, United States Marine Corps
B.S., United States Naval Academy, 2008

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

NAVAL POSTGRADUATE SCHOOL
December 2014

Author: William G. Wathen

Approved by: Robert A. Koyak
Thesis Advisor

Chad W. Seagren
Second Reader

Robert F. Dell
Chair, Department of Operations Research

THIS PAGE INTENTIONALLY LEFT BLANK

ABSTRACT

We develop statistical models to identify the most influential entry-level attributes of a Marine recruit to predict two performance measures: the Computed Tier Score and the time to achieve the rank of Corporal (E-4) in the 0621 Field Radio Operator Military Occupational Specialty (MOS). We use data collected from 2007 through 2014, on more than 1,100 Marines in the 0621 MOS to construct multivariate linear regression models to estimate Marines' Computed Tier Score and time to achieve E-4 based on their individual personal and professional attributes.

We find statistically significant relationships to exist between the entry-level attributes of a Marine recruit and the performance measures. The most influential predictor variables include the run time on the USMC Initial Skills Test (IST), number of crunches on the IST, rifle score, the Armed Services Vocational Aptitude Battery (ASVAB) General Technical (GT) score, ASVAB Clerical (CL) score, ASVAB General Science (GS) score, ASVAB Mathematics Knowledge (MK) score, ASVAB Paragraph Comprehension (PC) score, weight, and whether a Marine receives a weight waiver upon entrance into service. We recommend that new job performance measures be created for each high-density MOS in order to conduct further testing for MOS suitability.

THIS PAGE INTENTIONALLY LEFT BLANK

TABLE OF CONTENTS

LIST OF FIGURES

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF TABLES

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF ACRONYMS AND ABBREVIATIONS

AFQT	Armed Forces Qualification Test
AI	Auto Information
AIC	Akaike Information Criterion
AO	Assembling Objects
AR	Arithmetic Reasoning
AR	Auto & Shop Information
ASVAB	Armed Services Vocational Aptitude Battery
CAT	computerized adaptive test
CFT	Combat Fitness Test
CL	Clerical/ Administrative
CNA	Center for Naval Analyses
E-4	Corporal
EAS	End of Active Service
EI	Electronic Information
EL	Electronics
FROC	Field Radio Operator Course
FY	Fiscal Year
GED	General Educational Development
GS	General Science
GT	General Technical
HOPT	hands on performance test
HQMC	Headquarters Marine Corps
IMOS	Intended Military Occupational Specialty
IST	Initial Skills Test
ITS	Individual Training Standards
JKT	job knowledge test
JPM	Job Performance Measurement
LAR	Light Armored Reconnaissance
MAGTF	Marine Air Ground Task Force
M&RA	Manpower & Reserve Affairs

MC	Mechanical Comprehension
MCMAP	Marine Corps Martial Arts Program
MCO	Marine Corps Order
MK	Mathematics Knowledge
MOS	Military Occupational Specialty
MM	Mechanical Maintenance
NJP	Non-judicial Punishment
P&P	paper and pencil
PC	Paragraph Comprehension
PFT	Physical Fitness Test
PMOS	Primary Military Occupational Specialty
PRO	Proficiency
Q-Q	Quantile-Quantile
RSS	Residual Sum of Squares
SI	Shop Information
T&R	Training and Readiness
TFDW	Total Force Data Warehouse
TSS	Total Sum of Squares
USMC	United States Marine Corps
WK	Word Knowledge

EXECUTIVE SUMMARY

Each year, the United States Marine Corps (USMC) accesses thousands of new recruits into a variety of career fields, an assignment process that has significant implications for the USMC and the individual Marine's future career path. The USMC expends considerable manpower and time ensuring that annual Military Occupational Specialty (MOS) recruiting targets are met while trying to best match each recruit to those requirements. This research aims to provide the Marine Corps with an understanding of relationships between entry-level attributes of Marine recruits and two performance measures in order to better select the right recruits for each MOS. We develop statistical models to identify the most influential entry-level attributes of a Marine recruit in predicting two performance measures: the Computed Tier Score captured at the time of re-enlistment eligibility, and the time to achieve the rank of Corporal (E-4) in the 0621 Field Radio Operator MOS in the USMC.

Using data collected from 2007 through 2014 on more than 1,100 Marines in the 0621 MOS, multivariate linear regression models are developed to predict a Marine's Computed Tier Score and time to achieve E-4 based on their individual personal and professional entry-level attributes. These attributes, which include physical characteristics, test scores, physical fitness measures, education, and waiver information, comprise the independent variables in the study. This study answers the following questions:

1. Do significant relationships exist between entry-level attributes of a USMC recruit and the USMC Computed Tier Score or the time for a Marine to achieve the pay grade of E-4?
2. What are the most influential independent variables that predict the Computed Tier Score and the time to promotion to E-4 in a particular MOS field?
3. What insight does this analysis provide in terms of recommending changes to the current entrance criteria for the 0621 Field Radio Operator MOS?
4. What direction should a future study take to examine ways in which the matching of USMC recruits to MOS fields can be improved?

We find that statistically significant relationships do exist between the entry-level attributes of a Marine recruit and the USMC Computed Tier Score, as well as the time to achieve the pay grade of E-4 within the 0621 MOS in the USMC. Entry-level attributes of Marine recruits can be utilized to predict these dependent variables. Additionally, we recommend that this analysis be conducted on an annual basis, and not pooled into a multi-year study, at least into the near future.

The most influential predictor variables that allow prediction of the Computed Tier Score are found to be the Initial Skills Test (IST) run time, IST crunches, rifle score, the Armed Services Vocational Aptitude Battery (ASVAB) General Technical (GT) composite score, weight of a Marine, and whether a Marine received a weight waiver upon entrance into service. We find the most influential predictor variables for predicting the time to achieve the pay grade of E-4 to be IST crunches, IST run time, rifle score, the ASVAB General Science (GS) subscore, ASVAB Mathematics Knowledge (MK) subscore, ASVAB Paragraph Comprehension (PC) subscore, ASVAB Clerical/Administrative (CL) composite score, and whether a Marine receives a weight waiver upon service entrance. While IST crunches, IST run time, rifle score, and weight provide insight into the predicted time to achieve the pay grade of E-4, the variables GS, MK, PC, and CL_SCORE offer intriguing evidence that the USMC should further explore these variables for inclusion in the entrance criteria of a Field Radio Operator.

In order to explore other suitability to MOS measures that could lend to predicting a successful match, we have determined that there is a need for the development of new suitability measures. It is the recommendation of this study that new job performance measures be created for each high-density MOS in order to conduct further testing for MOS suitability. With the development of new success or job performance measures, this study can be replicated using the new job performance measures as the dependent variable for analysis.

ACKNOWLEDGMENTS

First, I would like to thank Dr. Robert Koyak for his continued support and devotion to my thesis. Without his knowledge, persistent guidance, and commitment, my work would not have been possible. I would also like the thank Major Chad Seagren for his steadfast assistance along the way.

I would like to thank Captain Andy Garrick and Tim Johnson at HQMC Manpower & Reserve Affairs for their guidance and support in my work.

Lastly, I would like to thank my family for standing beside me during this process, particularly my wife, Kelly, whose constant encouragement and dedication to our family during this time and throughout my military career continues to amaze me. To my daughters, Caroline and Lucy, thank you for continually reminding me of the most important things in life.

THIS PAGE INTENTIONALLY LEFT BLANK

I. INTRODUCTION

A. MOTIVATION AND OBJECTIVES

Each year, the United States Marine Corps (USMC) accesses thousands of new recruits into a variety of career fields; an assignment process that has significant implications for the USMC and the individual Marine's future career path. While the process takes into account both the recruit's preferences as well as the needs of the Marine Corps, it is clear that there is scope for making the assignment process more efficient. More specifically, there is continued desire to ensure that recruits are best matched to the right Military Occupational Specialty (MOS). Matching recruits to the MOS that they will most likely succeed and have a high level of performance improves not only the quality of each MOS as a community, but the USMC as a whole.

The USMC spends considerable manpower and time ensuring that annual MOS recruiting targets are met while trying to best match each recruit to those requirements. Currently, the USMC utilizes various entrance criteria to ensure that Marines are qualified to enter a specific MOS field. Headquarters Marine Corps (HQMC), D.C. Manpower and Reserve Affairs (M&RA) is investigating ways to improve the career field assignment process and seeks to explore the possible relationships between recruit attributes and potential indicators of success in the assigned MOS field.

This research aims to provide the Marine Corps with a better understanding of relationships between recruit attributes and possible indicators of success in a particular MOS in order better select the right recruits for the right MOS. Through identification of key attributes that lead to success, the USMC can modify the current MOS assignment process in order utilize the right human capital while meeting the needs of the Marine Corps. More specifically, entrance criteria for specific MOSs can be changed or validated to ensure the Marines with the highest likelihood of success are placed in the appropriate MOS. This research could also be used to help the USMC decide how to allocate recruits to specialties to meet numerical targets in those specialties.

B. FOCUS OF THE RESEARCH

The primary focus of this research is to develop a research concept, data collection plan, and repeatable methodology that improve M&RA's understanding of relationships between recruit attributes and their success within the assigned MOS. The end-state goal is to determine the entry-level recruit attributes that lead to the most success in specific MOSs in order to validate or recommend change to the current entrance criteria for high-density or priority-fill MOSs.

This study focuses specifically on the 0621 Field Radio Operator MOS, due to the stringency of the entrance requirements for this MOS, the technicality of the requirements necessary to perform successfully in the MOS, and existence of a significant yearly sample. During the course of this study, statistical models are constructed to estimate the relationships between entry-level attributes and two measures of perceived success within the 0621 MOS. The models are based on a set of variables or attributes that are available through a USMC Manpower database known as the Total Force Data Warehouse (TFDW).

Our investigation is organized as follows: First, we conduct exploratory analysis of the data to identify data characteristics and relationships, such as missing or invalid observations. We do this in order to obtain a basic understating of the relationships between variables. Next, we use linear regression to construct models to predict two possible dependent variables; time to achieve the pay grade of E-4 and the USMC Computed Tier Score. The Computed Tier Score is a quantitative performance metric that provides commanders an assessment of an individual Marine's performance for re-enlistment eligibility. Finally, we make recommendations for future study that will provide the most benefit to the career field assignment process.

This study answers the following study questions:

1. Do significant relationships exist between entry-level attributes of a USMC recruit and the USMC Computed Tier Score or the time for a Marine to achieve the pay grade of E-4?

2. What are the most influential independent variables that predict the Computed Tier Score and the time to promotion to E-4 in a particular MOS field?

3. What insight does this analysis provide in terms of recommending changes to the current entrance criteria for the 0621 Field Radio Operator MOS?

4. What direction should a future study take to examine ways in which the matching of USMC recruits to MOS fields can be improved?

C. ORGANIZATION OF THIS THESIS

This thesis is organized as follows. In Chapter II, we review literature on the career assignment process in the USMC, and we discuss the methodologies and findings of those studies. Additionally, Chapter II provides a detailed background into the current process for career assignment of enlisted Marines and an overview of the current MOS entrance criteria. Chapter III describes the data and methodology used to conduct this study. It includes a description of the data used for analysis and explanation of the data collection and cleansing process. Chapter IV discusses the results and analysis used in order to achieve those results. Chapter V provides conclusions of this study and recommendations for future work.

THIS PAGE INTENTIONALLY LEFT BLANK

II. BACKGROUND

A. THE PROCESS FOR CAREER ASSIGNMENT OF ENLISTED MARINES IN THE U.S. MARINE CORPS

Each branch of the Armed Services uses specific entrance criteria for screening recruits and assigning them to an MOS. Headquarters Marine Corps (HQMC) Manpower and Reserve Affairs (M&RA) conducts detailed analyses in order to determine the manning requirements for each MOS and to meet the current needs of the Marine Corps. Based on these manning requirements, recruits are then assigned into the required occupational specialties to match the demand. Prerequisites for entrance into specific MOS fields are defined in the Marine Corps Order (MCO) 1200.17E, the Military Occupational Specialties Manual (Short Title: MOS Manual) (USMC, 2013). The prerequisites for each MOS were originally constructed in order to try and match the best recruit to occupational field, but are not necessariliy updated when the job specialties change.

Traditionally, the Armed Services Vocational Aptitude Battery (ASVAB) composite test scores have been the most important deliniating factor in matching an individual to MOS. A recruit's test scores, background information (citizenship, security clearance eligibility, etc.), preferences, and the needs of the Marine Corps are considered in the determination of MOS assignments. Marine recruits are assigned an Intended MOS (IMOS) approximately two weeks prior to graduating basic training. They are then forwarded to their assigned MOS school for initial MOS training. Upon graduating from MOS school, each Marine is offically assigned his or her Primary MOS (PMOS) designator.

B. THE ARMED SERVICES VOCATIONAL APTITUDE BATTERY (ASVAB) AND MOS ENTRANCE CRITERIA

This section describes the Armed Services Vocational Aptitude Battery (ASVAB), which is a series of examinations that the Armed Forces use to set requirements to enter into service in the U.S. military. For the U.S. Marine Corps, the

ASVAB also determines entrance requirements that must be met in order to be assigned to a particular MOS.

1. ASVAB Components

The U.S. military has been screening potential recruits for aptitude since World War I. In 1976, all military services began using the ASVAB for both screening potential recruits for service entrance and assigning them to military occupations. Combining the selection and classification testing into one exam made the testing process more efficient while also enabling the military services to better match recruits to MOSs. The ASVAB has been revised many times in order to improve inefficiencies and problems with misnorming (History of Miltary Testing, n.d).

The ASVAB is comprised of ten subtests, each of which provides its own score. There are two versions of the ASVAB, a paper and pencil (P&P) version and a computerized adaptive test (CAT) version. The P&P-ASVAB combines two of the subtests, Auto Information (AI) and Shop Information (SI), into one single test, Auto and Shop Information (AR). These subtests are displayed in Table 1 (ASVAB Fact Sheet, n.d.).

Possible recruits are screened for entrance into the military by calculating a composite score, called the Armed Forces Qualification Test (AFQT). The AFQT is a composite score that incorporates the following four ASVAB subtests: Paragraph Comprehension (PC), Word Knowledge (WK), Mathematics Knowledge (MK), and Arithmetic Reasoning (AR). The AFQT score is reported as a percentile between 1–99, which indicates the percentage of examinees that scored at or below the percentile score (ASVAB Scoring, n.d.). The current minimum AFQT score for entrance into the USMC is 32 for high school graduates and 50 for persons with a GED (ASVAB Scoring, n.d.).

Table 1. ASVAB subtests (after ASVAB Fact Sheet, n.d.)

Test	**Description**
General Science (GS)	Knowledge of physical and biological sciences
Arithmetic Reasoning (AR)	Ability to solve arithmetic word problems
Word Knowledge (WK)	Ability to select the correct meaning of a word presented in context and to identify best synonym for a given word
Paragraph Comprehension (PC)	Ability to obtain information from written passages
Mathematics Knowledge (MK)	Knowledge of high school mathematics principles
Electronic Information (EI)	Knowledge of high school mathematics principles
Auto Information (AI)	Knowledge of automobile technology
Shop Information (SI)	Knowledge of tools and shop terminology and practices
Mechanical Comprehension (MC)	Knowledge of mechanical and physical principles
Assembling Objects (AO)	Ability to determine how an object will look when its parts are put together

2. MOS Entrance Criteria

The Marine Corps uses four other composite scores derived from the ASVAB subtest scores for determining entrance or assignment for recruits into occupational specialties. The four USMC composite scores are General Technical (GT), Mechanical Maintenance (MM), Electronics (EL), and Clerical/Administrative (CL). Each composite score is formulated from a combination of various ASVAB subtest scores (USMC, 2009). The composite scores and their derivations are shown in Table 2.

Table 2. U.S. Marine Corps ASVAB composite scores (after Classification Testing, 2009)

Composite Scores	**Score Derivation**
General Technical (GT)	WK + PC + AR + MC
Mechanical Maintenance (MM)	AR + EI + MC + AS
Electronics (EL)	AR + MK + EI + GS
Clerical/ Administration (CL)	WK + PC + MK

The U.S. Marine Corps assigns recruits to a particular MOS based on specific entrance criteria or prerequisite requirements. These entrance criteria vary by MOS, and are set to best match recruits with the right skill sets, knowledge base, physical ability, and aptitude levels to a corresponding MOS. The job descriptions, prerequisite requirements, and MOS requirements for each MOS are outlined in MCO 1200.17E Military Occupational Specialties Manual (Short Title: MOS Manual) (USMC, 2013). Descriptions, prerequisites, and requirements for the 0621 MOS (Field Radio Operator) and the 0311 MOS (Rifleman) are outlined by the MOS Manual as follows:

MOS 0621, Field Radio Operator PMOS

a. MOS Description: Field Radio Operators employ radios to send and receive messages. Typical duties include the set up and tuning of radio equipment including antennas and power sources; establishing contact with distant stations; processing and logging of messages; making changes to frequencies or cryptographic codes; and maintaining equipment at the first echelon. Skill progression training for Sergeant and Corporal is Radio Supervisors Course.

b. Prerequisites
(1) Must be a U.S. Citizen.
(2) Must possess an EL score of 105 or higher.
(3) Must possess a valid state driver's license.
(4) Security requirement: Secret security clearance eligibility.

c. Requirements. Complete the Field Radio Operator (FROC) Course (after USMC, 2013).

MOS 0311, Rifleman PMOS

a. MOS Description: The Riflemen employ the modern service rifle/carbine, the M203 grenade launcher and the squad automatic weapon (SAW). Riflemen are the primary scouts, assault troops, and close combat forces available to the Marine Corps Air Ground Task Force (MAGTF). They are the foundation of the Marine infantry organization, and as such are the nucleus of the fire team in the rifle squad, the scout team in the LAR squad, scout snipers in the infantry battalion, and reconnaissance or assault team in the reconnaissance units. Noncommissioned Officers are assigned as fire team leaders, scout team leaders, rifle squad leaders, or rifle platoon guides.

b. Prerequisites. Must possess a GT score of 80 or higher.

c. Requirements. Complete the Marine Rifleman Course at the School of Infantry (after USMC, 2013).

These two MOS descriptions are provided to emphasize that each USMC MOS has different job descriptions, prerequisites, and requirements. For the purposes of this study, it is important to note the prerequisite requirements for entrance into a specific MOS. These prerequisites are the criteria that the USMC uses to classify a recruit into an MOS.

C. LITERATURE REVIEW

This section reviews previously conducted studies on career assignment and related subjects that are of interest to the manpower community. More specifically, studies in the following areas are reviewed: military career assignment and the relationship between ASVAB testing and performance in an MOS.

1. Previous Studies on Career Assignment

Rautio (2011) examines standards used to screen recruits for assignment to the communications field in the USMC. He discusses the relationship between ASVAB composite scores and success measures at the communications occupational field schools. The data used for analysis covers 9,921 Marines from fiscal year 2006 through fiscal year 2009. The author develops multivariate probit regression models that include all four years of data encompassing multiple MOS fields. The probit models determine the effects of ASVAB composite scores and other measures of performance on success at the communications schools (Rautio, 2011).

Rautio (2011) considers models that use the following predictor variables: Gender, Race, Ethnicity, Marital Status, Number of Dependents, Primary MOS, Fiscal Year, Armed Forces Qualification Test (AFQT) Score, ASVAB composite scores, Education Level, Proficiency Score, and Conduct Score. The dependent variable identifies whether a Marine successfully completed the initial communications MOS school. Rautio (2011) finds that the ASVAB Electronic composite score (EL Score) has a significantly positive effect on the probability of success at the communications schools. The author also cites other variables that have a positive effect on the probability of success such as marital status, ethnicity, and the ASVAB Clerical composite test score. He also finds that gender and education level are statistically significant contributors to the prediction of success.

2. Studies on the Relationship between ASVAB Testing and Performance in an MOS

The Center for Naval Analyses (CNA) conducted a multi-year study (Carey, 1993) for the Marine Corps Job Performance Measurement (JPM) project in order to construct valid measures for job performance and to determine the relationship between the ASVAB and Marine job performance. The study was conducted due to concern by Congress that a significant number of unqualified and low aptitude personnel had entered into military service during the 1970s. This concern was supported by CNA studies that discovered a misnorming of the ASVAB that resulted in 360,000 recruits entering into service that would have been declared ineligible if the ASVAB test scores had been accurate. In 1981, Congress mandated that each service perform a Job Performance Measurement (JPM) project in order to relate ASVAB scores to on-the-job performance (Carey, 1993). This study develops new measures for performance and success in order to study the relationships to predictor variables.

CNA executed two phases of the study between 1986 and 1990. The first phase, (1986 to 1987) focuses on job performance measurement for infantry MOSs. The second phase (1990) focuses on job performance measures for the mechanical maintenance field (Carey, 1993). Our discussion is limited to the infantry MOS phase of the study.

The infantry MOS study maps the job duties of five infantry MOSs based on the Marine Corps Individual Training Standards (ITS), now included in the USMC Training and Readiness (T&R) Manual, for infantry occupations. The study proposes job performance measures, hands-on performance tests (HOPTs) and job knowledge tests (JKTs) that were developed to directly test job duties as outlined by the ITS. Carey (1993) finds that the HOPTs proposed by CNA were effective measures of job performance due to their strong agreement with actual job performance based on the requirement that an examinee perform job-related tasks under realistic but standardized conditions. The JKTs are designed to be a parallel test to the HOPTs and include written exam knowledge testing of items related to job performance. This study notes that standardized HOPTs are expensive and difficult to develop and implement. CNA concludes that while the HOPTs should serve as the benchmark for measuring job performance, JKTs provide promising replacements for setting enlistment standards. Marine Corps Proficiency marks (PRO marks) are also considered in the study but found to provide less fidelity to actual job performance when compared to the HOPTs and JKTs (Carey, 1993).

In an earlier CNA study, Mayberry (1990) investigates the relationship between these JPMs and ASVAB composite scores, with particular focus on the General Technical (GT) composite score. Mayberry focuses primarily on the GT score because the Marine Corps uses this score to determine eligibility for the infantry occupational field.

More than 2,300 infantrymen from five infantry MOSs were tested over the course of two days. Examinees were administered both the JKTs and the HOPTs. The results from the performance testing are then modelled in order to determine if relationships exist between aptitude, as indicated by the ASVAB composite scores, and MOS performance.

Mayberry (1990) finds a strong relationship between individual aptitude level and later performance of critical MOS tasks. This study provides a useful measure of MOS performance and determines that the ASVAB composite scores provide significant indicators of performance within an MOS.

D. CHAPTER SUMMARY

The U.S. Marine Corps MOS Assignment Process attempts to assign the most qualified recruits with the most potential for success to the right MOS. The USMC uses entrance criteria to assign those recruits to an MOS while meeting the needs of the Marine Corps. Based on the literature reviewed, ASVAB composite scores lend well in predicting success during MOS school and within the assigned MOS. Additionally, these studies suggest that the EL composite score is good predictor of performance in the 0621 Field Radio Operator MOS. Our study focuses on predicting success or performance in a specific MOS while in the operating forces.

III. DATA AND METHODOLOGY

A. THE DATA

This section gives a detailed explanation of the data collection process, the original data gathered for study purposes, and the preparation of the data in order to conduct a useful analysis.

1. Data Summary

The data used in our research is obtained from the USMC's Total Force Data Warehouse (TFDW). TFDW is a database of personnel records for Manpower & Reserve Affairs. TFDW contains historical information for active duty and reserve Marines in the USMC. For the purposes of this study, data is pulled from TFDW for all active duty enlisted Marines with the 0621 MOS designator that entered into active service during the Fiscal Years of 2008 through 2010, or from 1 October, 2007 through 30 September, 2010.

The data includes personal and professional information including physical characteristics, physical fitness performance scores, education information, demographics, waivers received, ASVAB test scores, promotions, marksmanship scores, and legal information. The data provides a snapshot in time of the Marine's career profile that is updated when there is a change to the information, while other data fields are populated each month. Lastly, there are data fields that are populated only once, such as information gathered upon entering service. Table 3 gives details on the initial sample obtained for this study. Duplicate observations were removed and determined to be present due to changes in enlistment dates, but do not affect other fields.

Table 3. Summary of Marines entering service in FY2008–FY2010 for the 0621 MOS

Fiscal Year	Observations in Original Sample	Sample with duplicates removed
FY2008	429	377
FY2009	433	384
FY2010	510	466

2. Data Formatting and Cleaning

This section explains the procedures taken to prepare the data for analysis including an explanation of the observations that were removed from the analysis and the grouping of categorical variables.

a. Observation Removal, Variable Substitution, and Censoring

In order to properly build relevant analytical models, the historical information for each Marine's record should contain complete information for each of the predictor variables. When missing or invalid information exists for a predictor variable, we remove those records from the analysis.

When there are missing values for the dependent variables included in the study, we first determine if there is a valid reason and possible substitution value for the variable. If no valid substitute exists, the records with missing values are removed. Reasons for missing values include Marines separated from service prior to the conclusion of their enlistment and deployment waivers. These exclusions are shown in Table 4.

The first dependent variable considered, the Computed Tier Score is calculated as a combination of seven sub-variables. The Computed Tier Score is discussed in greater detail later in this chapter. One of the sub-variables of the Computed Tier Score, martial arts belt level, contains missing values in the data for 2008 and 2009. We decided to replace these missing values with the belt level closest to the median belt level of all records. We assume that each Marine has received, at minimum, the median belt level due to USMC requirements to achieve certain belt levels during career progression. Additionally, this assumption has minimal impact on the overall values of Computed Tier Score, but allows us to include more observations for analysis. The number of observations with a substitute value for martial arts belt level is included in Table 4. Fiscal Year 2010 did not contain any observations that required substitution for martial arts belt level.

The second dependent variable included in the analysis is the time in days that it takes for a Marine to promote to the pay grade of E-4, or time2E4. After removal of records for Marines separated from active service, missing values still exist for Marines that are not promoted to E-4 prior to completion of their first four years of active service. Although these Marines never achieved the pay grade of E-4 during their period of observation in the study, a censored value is substituted for these records for time2E4 in order to retain these important observations for study. The censored time2E4 value is equal to one plus the maximum observed time for the cases that we considered, which is 1570 days. Twenty records from the FY2010 data (approximately five percent of the total number of records) have time2E4 set to this censoring value. Figure 1 shows a histogram of time2E4 for the FY2010 data, in which the twenty censored values are apparent at the far right. These values would be a continuation of the right-hand tail if the values were not censored. The numbers of observations with censored values for time2E4 for each year of study are shown in Table 4.

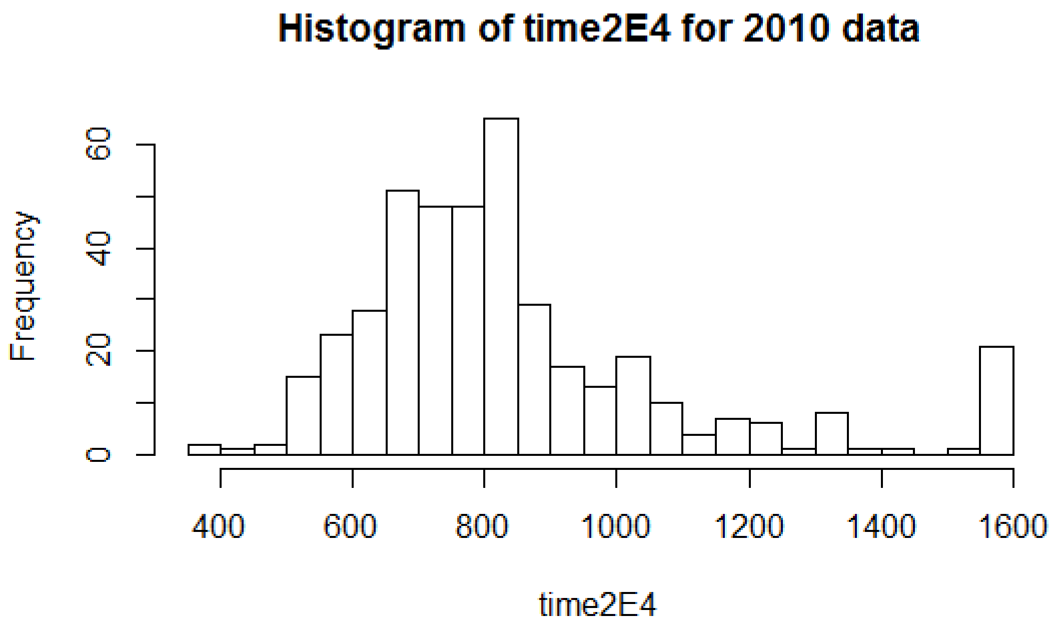

Figure 1. Histogram of the number of days to promotion to the pay grade of E-4 (time2E4) for FY2010 entries to the 0621 MOS

Table 4. Summary of data formatting and cleaning

Fiscal Year	Total Observations	Observations Removed due to separation from service	Observations used in Analysis	Observations with substitute value for martial arts belt level	Observations with censored time2E4
2008	377	26	351	23	32
2009	384	30	354	14	25
2010	466	45	421	0	20

With the removal of observations from the data set as described above, the remaining data set consists of 1,126 Marines across three fiscal years.

b. Grouping of Categorical Data

The categorical variables considered for analysis were screened to ensure they contained a sufficient number of different categories for use as potential predictor variables.

3. Assumptions and Limitations of the Data

One of the purposes of this study is to analyze the process of career assignment in order provide valuable recommendations for future occupational classification. It is the intention of this study that the modeling techniques and recommendations be suitable for the current manpower selection and assignment process in the USMC. Therefore, we seek to develop modeling techniques and supporting methodology that can be applied to a broad range of MOSs, particularly the high-density MOSs, in order to gain a better understanding of the overall picture of career placement. This study focuses on the 0621 Field Radio Operator MOS. We do not consider an optimization problem placing recruits into the various MOSs; instead, we focus on the entry attributes that may indicate a successful match with an occupation.

The Marine Corps uses the Computed Tier Score for re-enlistment purposes. The Computed Tier Score is a quantitative measurement for re-enlistment eligibility. This study does not attempt to evaluate the validity of the Computed Tier Score as a measure of performance or re-enlistment suitability.

B. VARIABLE DESCRIPTIONS

This section provides descriptions of the variables considered for analysis. All variables that have potential for correlation with success, re-enlistment, and MOS suitability are included. Additionally, only those variables obtainable through TFDW are analyzed.

1. Dependent Variables

The dependent variables considered for analysis are the USMC Computed Tier Score and time (in days) to promote to the pay grade of E-4, or Corporal, in the USMC.

a. Computed Tier Score

The USMC uses two measures for determining eligibility for re-enlistment, the Computed Tier Score and the Commander's Tier Recommendation. The Computed Tier Score was originally introduced in May 2011 through MARADMIN 273/11. It was created in order to provide commanders a quantitative assessment of an individual Marine's performance. The Computed Tier Score is calculated using the scores from a Marine's physical fitness test (PFT), combat fitness test (CFT), proficiency and conduct markings, and the rifle range qualification score. Additionally, points are awarded for USMC martial arts belt level and for meritorious promotions to the current rank. The Computed Tier Score is then compared to all Marines within the same MOS that are eligible for re-enlistment during the same fiscal year. An example of a Marine Corps Tier Worksheet is shown in Figure 2.

CPL I. M. MARINE		
PMOS 0621		
Event	MOS Avg (as of 02-08-2012)	SNM's Scores
PFT	246	274
CFT	282	284
Proficiency	430	430
Conduct	430	430
Rifle	293	303
MCMAP	MMB - Tan Belt	MMD - Green Belt
Meritorious Promotion	N/A	0
	1691	1751
Legal History	Type	Date
0 NJP(s)	N/A	N/A
Tier Chart		
Tier I (10%) 91%-100%		
Tier II (30%) 61%-90%		
Tier III (50%) 11%-60%	X	
Tier IV (10%) 1%-10%		

Figure 2. USMC Tier Worksheet (after GySgt B. Lodge, USMC, Personal Communication, September 10, 2014).

The raw scores from the PFT, CFT, and Rifle Qualification are not weighted or altered in the calculation of the Computed Tier Score. The Proficiency and Conduct markings are multiplied by 100, and each Marine Corps Martial Arts Program (MCMAP) belt level is associated with a specific point value when added to the total score. Finally, Marines that have been meritoriously promoted to their current rank receive an additional 100 point bonus, as long as they have no misconduct on their record within the previous six months of promotion (GySgt B. Lodge, USMC, Personal Communication, September 10, 2014). These point values are then summed together for the final calculation of the Computed Tier Score. As seen in Figure 2, Marines are then evaluated against their re-enlistment cohort and placed into Tiers 1-4, based on their respective percentile. For the purposes of this study, we use the non-categorized Computed Tier Score as a quantitative variable for analysis.

In order to calculate the Computed Tier Score for each Marine or observation in the study, we capture the data for each component and generate the score using the aforementioned algorithm. All data captured for the computation of the Computed Tier Scores are taken on July 1 of the fiscal year prior to a Marine's end of active service (EAS). This data is chosen because it marks the first day that Marines can apply for re-enlistment, and mirrors the process that the USMC uses to offer re-enlistment.

b. Time to Achieve E-4

The second dependent variable we consider is time (in days) to achieve the pay grade of E-4, or Corporal, in the USMC. We choose this metric due to the high significance of achieving this rank in the USMC and the possible correlation to performance within a Marine's specific MOS. This variable is referred to as time2E4 in the regression model outputs used in the analysis.

2. Independent Variables

Table 5 contains a list of all independent variables that were considered in this study.

Table 5. Description of independent variables used in analysis

Variable Name	Type	Description
AGE	Numerical	Age of Marine upon entering service
GENDER	Categorical	Gender of Marine
HEIGHT	Numerical	Height upon entering service
WEIGHT	Numerical	Weight upon entering service
IST_CRUNCHES	Numerical	Number of crunches for Initial Skills Test
IST_RUN	Numerical	Run time (in seconds) for 1.5 Mile run for Initial Skills Test
RIFLE_SCORE	Numerical	Initial Rifle Score during Basic Training
WAIV_TRAFFIC	Binary	Received waiver for having a traffic related offense prior to service
WAIV_MINOR.NONTRAFF	Binary	Received waiver for a minor-non traffic related offense prior to service
WAIV_MISCOND	Binary	Received waiver for a misconduct offense prior to service
WAIV_DRUGSUBST	Binary	Received waiver for Drug or Substance usage prior to service
WAIV_WEIGHT	Binary	Received waiver for being over weight requirement prior to service
WAIV_ICD9	Binary	Received waiver for Medical reasons
WAIV_OTHER	Binary	Received waiver for other reasons not captured
GS	Numerical	ASVAB GS subscore
MK	Numerical	ASVAB MK subscore
PC	Numerical	ASVAB PC subscore
AR	Numerical	ASVAB AR subscore
AS	Numerical	ASVAB AS subscore
WK	Numerical	ASVAB WK subscore
MC	Numerical	ASVAB MC subscore
EI	Numerical	ASVAB EI subscore
GT_SCORE	Numerical	ASVAB GT composite score
MM_SCORE	Numerical	ASVAB MM composite score
CL_SCORE	Numerical	ASVAB CL composite score
EL_SCORE	Numerical	ASVAB EL composite score

C. METHODOLOGY

This section explains the techniques used to conduct the statistical analyses, variable transformations, variable selection methods, and model validation techniques. The following concepts are basic to fitting linear models and the reader is referred to a reference such as (Faraway, 2005) for further statistical understanding.

1. Multivariate Linear Regression

In order to address our study questions, we use statistical models to determine if a significant relationship exists between the independent variables and the dependent (response) variable. The response variables in this study are continuous, and are analyzed separately against the independent variables. Multivariate linear regression models are used for explaining the relationship between a single dependent variable Y, commonly called the response, and multiple independent variables (predictors), $X_1, ..., X_p$ (Faraway, 2005, p. 6).

In a linear regression model, the continuous response variable Y is modeled in terms of p independent variables $X = \{x_{1,} x_2, ..., x_p\}$. The general form for a multivariate linear regression model is:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_p x_p + \varepsilon$$

where $\beta = \{\beta_0, \beta_1, ..., \beta_p\}$ are unknown parameters, or coefficients, that are associated with the independent variables. β_0 is the intercept term, and ε is the prediction error, or random error term that has no relationship to X (Faraway, 2005, p. 11).

2. Variable Transformation

Transforming the dependent or independent variables can often improve the fit of a model and correct violations of model assumptions. It is important to explore the possibility of improving a model by transforming the variables included, particularly the dependent variable. While transforming the variables used in analysis may make the results difficult to interpret upon initial inspection, it can provide a better model fit (Faraway, 2005).

The Box-Cox transformation family is used in our study to determine an appropriate transformation of the response variable. The Box-Cox family transforms the independent variable $y \to g_\lambda(y)$ where the transformation indexed by λ is as follows (Faraway, 2005, pp. 110-111):

$$g_\lambda(y) = \left\{ \frac{y^\lambda - 1}{\lambda}, \; when\, \lambda \neq 0 \right.$$
$$g_\lambda(y) = \left\{ \log(\lambda), \; when\, \lambda = 0 \right.$$

The best values of λ and the regression parameters are determined using maximum likelihood.

3. Variable Selection

In developing statistical models, it is important to consider variable selection in order to determine the best subset of independent variables to be included the model. Introducing too many independent variables ("overfitting") reduces the overall predictive power of the model. In order to find the best set of independent variables for analysis and to reduce the possibility of overfitting, we use Best Subsets Regression (Faraway, 2005, pp. 127-128). Best Subsets Regression finds the best set of predictors for a given subset size, and then chooses the subset size to optimize a criterion such as adjusted R^2. Adjusted R^2 is defined as follows (Faraway, 2005, p. 127):

$$R_a^{\,2} = 1 - \frac{RSS/(n-p)}{TSS/(n-1)}, \; where$$
$$RSS = residual\; sum\, of\; squares = \sum (\hat{y} - y)^2$$
$$TSS = total\; sum\, of\; squares = \sum (y - \bar{y})^2$$

where, n is the number of observation in the data set, and p is the number of predictor variables in the initial model.

Cross validation can be used to select the subset size. This is done by randomly selecting a given percentage of the data (e.g. ten percent), fitting the model on the remaining set of data, and then calculating the sum of squares for using the model to predict the first set. This procedure can be repeated many times to obtain a better estimate of how well the model is able to predict new data. The number of predictor variables used in the model is selected to minimize the estimated mean squared prediction error. We use Best Subsets Regression with cross-validation, taking out a randomly selected subset of ten percent of the observations each time for use as a test set, repeating this procedure ten times.

4. Regression with a Censored Outcome Variable

We consider regression using the number of days for a Marine to be promoted to the pay grade of E-4 (time2E4) as an outcome variable. As we discussed in section A(2)(a) above, in a number of cases the Marine did not achieve this promotion in the observable time period. These cases are "right censored" with the maximum observable time used to represent these values. Their actual promotion times are greater than the censored values. A regression model with censored values in the outcome variable can be estimated taking censoring into account. We use the survreg function in the survival package in R to fit these models. Because diagnostic tools are much better developed for uncensored regression, we use uncensored regression first and then compare the results to those obtained using the survreg function.

5. Model Validation

It is important to validate a statistical model to ensure that the model provides meaningful results. This section explains the techniques used to validate the linear regression models.

The validity of the regression model depends on adherence to several key assumptions. These model assumptions need to be validated using regression diagnostics. The model assumptions are listed as follows:

1. The errors are independent, exhibit constant variance, and are normally distributed.
2. The structural part of the model is correct.
3. Unusual observations are not overly influential in the model (Faraway, 2005, p. 53).

The regression diagnostics are conducted using a set of diagnostic plots that allows for examination of these model assumptions.

6. Software Used for Analysis

The R programming language is used (R Development Core Team, 2014) for the analyses performed in this study.

D. CHAPTER SUMMARY

This chapter provides a detailed explanation of the data and methodologies used in order to conduct this analysis. Data formatting, observation removal, and data cleaning procedures are utilized in order to prepare the data for viable statistical modeling. The independent and dependent variables for consideration are modeled using multivariate linear regression while considering necessary variable transformations. Finally, the variable selection methods and model validation techniques are outlined for use in directing this analysis.

IV. RESULTS AND ANALYSIS

We present the results of fitting the statistical models that are described in Chapter III. Two response variables are considered separately: the Computed Tier Score calculated near the time that Marines are eligible for re-enlistment (about 2.5 years into the initial enlistment); and, the number of days required for an enlistee to make promotion to the pay grade of E-4. These response variables are taken as measures of success of an enlistee's placement in the 0621 MOS. For both response variables, we use data on USMC first enlistments in the 0621 MOS for FY2010. This is the most recent data available to us, and we also have found it to be the most reliable. We also explore using a multi-year model that includes data on all entries from FY2008 to FY2010.

A. COMPUTED TIER SCORE ANALYSIS

In this section we present the results of fitting a regression model to predict the Computed Tier Score from a set of explanatory variables obtained at the initial point of enlistment, using data for FY2010 entries. The independent variables used in all regression analyses are described in Table 5.

1. Initial Variable Relationship Exploration

Figure 3 shows a series of plots that provide an initial look at the nature of the relationships between each independent variable and the Computed Tier Score. The red line in each plot is a regression trend line that describes the mean-relationship between the two variables.

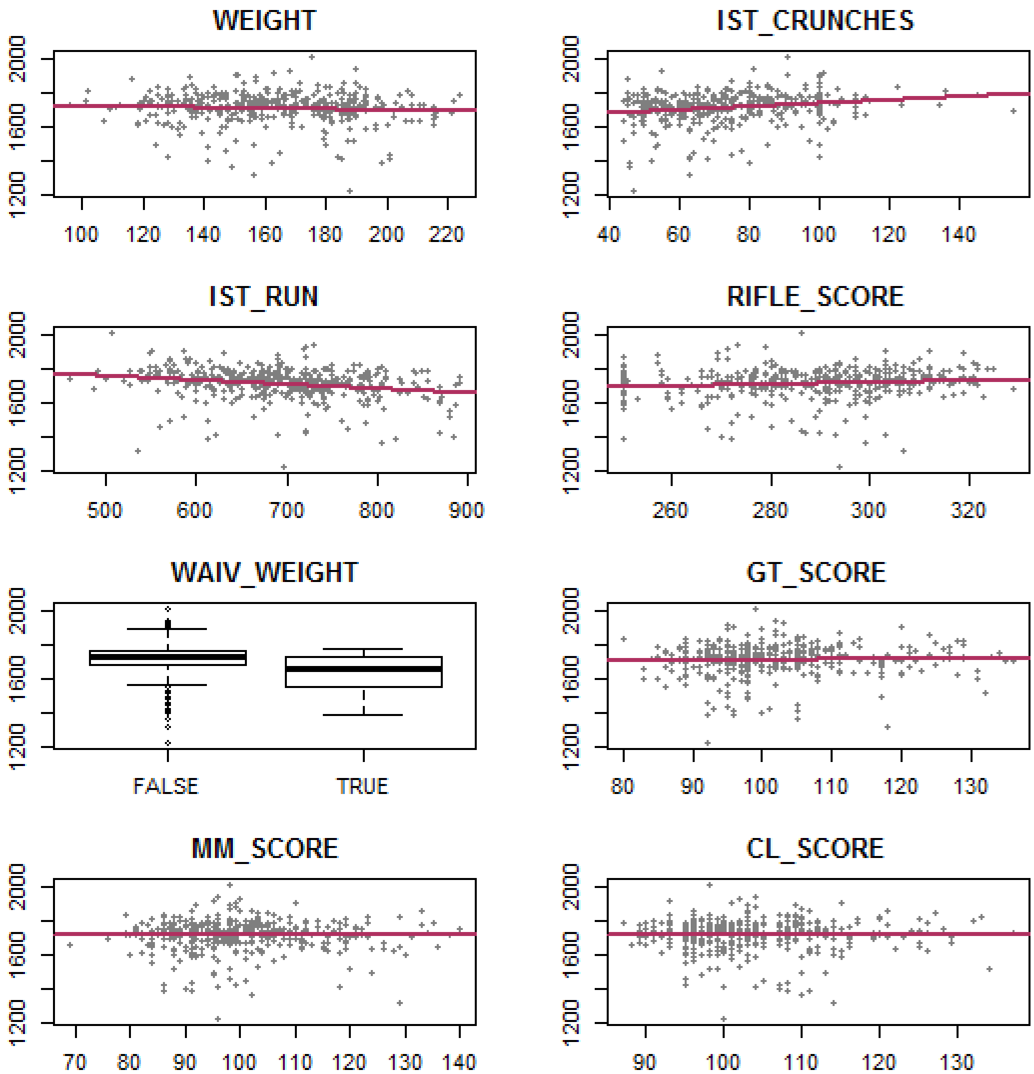

Figure 3. Initial variable relationships to Computed Tier Score for the FY2010 data

Note: Computed Tier Score is on the vertical axis of each plot, and each independent variable is on the horizontal axis.

An initial observation of the relationships between Computed Tier Score and the independent variables suggests the presence of possible relationships between variables. For example, the upward trend of the red regression line in the IST_CRUNCHES plot indicates that as the number of crunches increases, the Computed Tier score increases. Similarly, as the IST_RUN time increases, the Computed Tier Score decreases.

2. Evaluation of the Regression Model

We explore the possibility that the response variable, Computed Tier Score, may need to be transformed in order to better satisfy the assumptions of a linear regression model. To do this we use the Box-Cox transformation method described in Chapter III in order to determine if a transformation of the dependent variable would be appropriate. For this model, the Box-Cox method produces an estimated exponent of $\hat{\lambda} = 5.6$ which is extreme given that the numerical scale of Computed Tier Score is in the low thousands. This result suggests that the Box-Cox family of transformations cannot provide a useful resolution of the dependent varaible as discussed in Faraway (2005). We decide not to transform the dependent variable in this case, accepting that by not doing so the error terms may not be approximately normally distributed, which requires a greater exercise of care to guard against the effects of outliers and other influential observations.

We begin with all 18 possible predictor variables listed in Table 5, excluding the ASVAB subscores. Variable selection using Best Subsets Regression with cross-validation is performed in order to find a near-optimal model based on the original set of independent variables as discussed in Chapter III. When conducting cross-validation, we find the optimal model to contain five predictor variables, including WEIGHT, IST_CRUNCHES, IST_RUN, RIFLE_SCORE, and WAIV_WEIGHT. We then find the best subset that maximizes adjusted R^2 in order to include variables that are highly regarded as entrance criterion into an MOS in the USMC. The best subset size contains eight predictor variables. The resulting model is summarized in Figure 4.

```
lm(formula = Tier ~ WEIGHT + IST_CRUNCHES + IST_RUN + RIFLE_SCORE +
    WAIV_WEIGHT + GT_SCORE + MM_SCORE + CL_SCORE, data = Master10)

Residuals:
    Min      1Q  Median      3Q     Max 
-455.34  -33.64    7.38   47.42  245.74 

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)    
(Intercept)    1769.18820   96.98545  18.242  < 2e-16 ***
WEIGHT           -0.34523    0.17437  -1.980  0.04839 *  
IST_CRUNCHES      0.62392    0.23601   2.644  0.00852 ** 
IST_RUN          -0.20447    0.05594  -3.655  0.00029 ***
RIFLE_SCORE       0.46530    0.23745   1.960  0.05072 .  
WAIV_WEIGHTTRUE -65.00997   22.68478  -2.866  0.00437 ** 
GT_SCORE          2.13337    1.00373   2.125  0.03414 *  
MM_SCORE         -1.38329    0.70565  -1.960  0.05063 .  
CL_SCORE         -1.14032    0.74311  -1.535  0.12567    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 87.18 on 412 degrees of freedom
Multiple R-squared:  0.1273, Adjusted R-squared:  0.1103 
F-statistic: 7.509 on 8 and 412 DF,  p-value: 2.273e-09
```

Figure 4. Computed Tier Score model output

In Figure 4, the "Estimate" column shows the regression coefficients for each corresponding predictor variable, while the "Pr(>|t|)" column gives the associated p-values for each estimate. A p-value of less than 0.05 suggests that the variable is statistically significant, and should be included in the model.

The model from Figure 4 includes 421 records and eight predictor variables from the 2010 data set. Table 6 shows the descriptive statistics for the seven continuous variables included in the model. The descriptive statistics shown are mean, median, standard deviation, minimum value, and maximum value. The only binary variable included in the model is WAIV_WEIGHT, with 405 Marines (96.2 percent) not assigned a weight waiver and 16 Marines (3.8 percent) receiving a weight waiver before entering active service.

Table 6. Descriptive statistics for the quantitative variables used in Computed Tier Score analysis

Variable	**Mean**	**Median**	**Standard Deviation**	**Minimum**	**Maximum**
WEIGHT	161.90	161	25.62	96	224
IST_CRUNCHES	75.41	73	19.51	44	155
IST_RUN	690.90	690	83.66	460	892
RIFLE_SCORE	287.50	290	19.42	250	329
GT_SCORE	101.80	99	10.40	80	136
MM_SCORE	100.20	98	11.89	69	140
CL_SCORE	103.40	101	8.87	87	137

We explore the necessity for non-linear transformations of the independent variables using partial residual plots (Faraway, 2005). We use cubic basis splines with four interior knots in order to determine if a non-linear transformation of the predictor variables would improve the model. A convenient class of transformations to consider for this purpose is cubic splines with interior knots placed at the 10th, 30th, 50th, and 70th percentiles of a variable. When used with variable transformations, these plots along with 95 percent confidence bands suggest the types of transformations that are plausible for the predictor variables. For example, if a straight line fits within the confidence bands, it is unlikely that a nonlinear transformation is needed to bring out the explanatory power of the variable in question. The resulting partial residual plots are shown in Figure 5. It is clear that straight lines can be fit within the confidence bands of each of these plots, which suggests that a simple linear model formulation should be adequate. We confirm this by conducting an F-test, with (42,370) degrees of freedom in order to compare the results from a model with variable transformation versus a model without transformation. The resulting F-statistic is 0.9534 with a p-value of 0.5574. This comparison indicates that the model with transformations is not significantly different than the model without transformation at the $\alpha = 0.05$ test level. Therefore, we do not reject the null hypothesis and conclude that non-linear transformation of the predictor variables is not necessary.

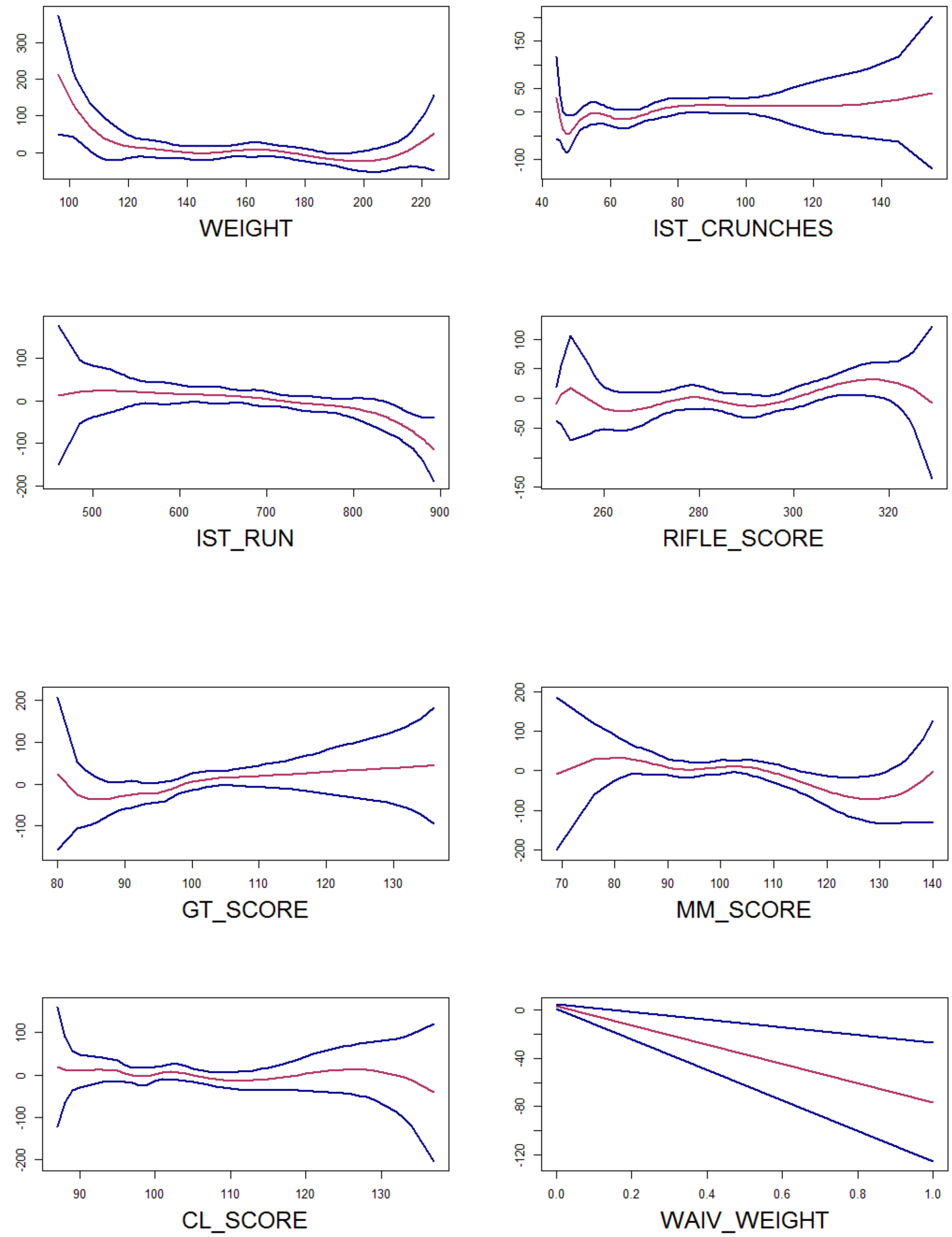

Figure 5. Partial residual plots of the predictor variables used in the analysis of Computed Tier Score

Note: The red line is the cubic regression spline, and the blue lines are 95 percent confidence bands. If a straight line fits between the blue confidence bands, a good indication of a linear relationship exists.

The regression diagnostics are displayed in Figure 6 using a set of diagnostic plots that allow for examination of the model assumptions.

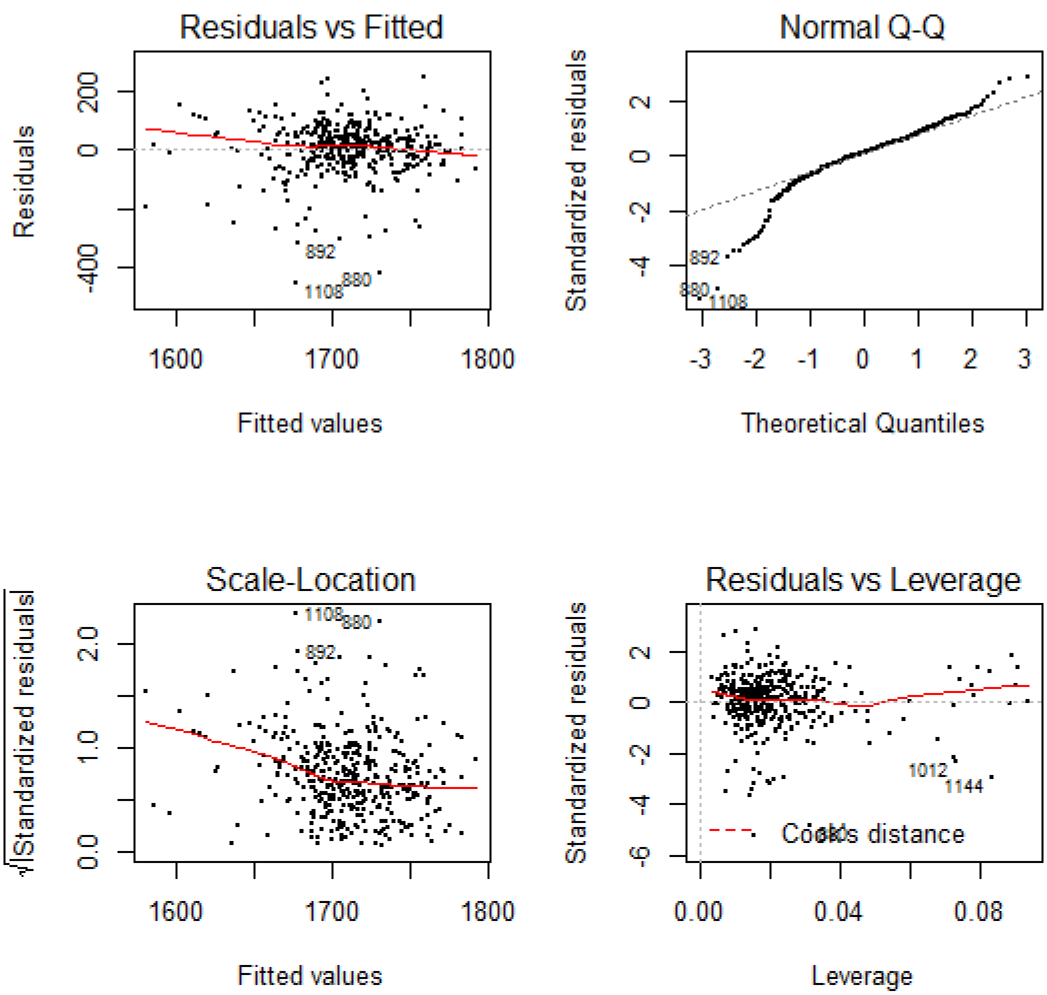

Figure 6. Computed Tier Score model diagnostics

As shown in Figure 6, the Residuals vs. Fitted plot shows no obvious patterns of unequal spread about the x-axis, thus indicating that the residuals exhibit constant variance. The Normal Q-Q plot indicates a presence of heavier than normal tails, and exhibits possible signs of non-normality. The Residuals vs. Leverage plot shows no indication of overly influential data points in the model. In other respects, the model diagnostics indicate that the model assumptions are not violated.

3. Explanation of the Model Results

From the model fit in Figure 4, we determine that the most significant predictor variables are IST_RUN, WAIV_WEIGHT, and IST_CRUNCHES. Additionally, WEIGHT and GT_SCORE narrowly meet the 0.05 p-value threshold for inclusion in the model. MM_SCORE and CL_SCORE exhibit interesting relationships to Computed Tier Score, indicating that with a higher score in either test, the predicted Computed Tier Score actually decreases. This model provides statistically significant predictability for measuring success in terms of Computed Tier Score.

B. ANALYSIS OF THE TIME TO ACHIEVE E-4 USING ALL POSSIBLE PREDICTOR VARIABLES INCLUDING ASVAB SUBSCORES

The second dependent variable we consider in this analysis is the time it takes in days for a Marine to achieve the pay grade of E-4, and is referred to as time2E4 in this study. The remaining models in this study focus exclusively on analyzing the entry-level attributes of a Marine recruit against this dependent variable.

Upon initial observation and variable correlation exploration, we determine that the ASVAB subscores are highly correlated with the ASVAB composite scores. This observation makes sense, given that the composite scores are derived from the subscores. Therefore, we perform two separate linear regressions in order to accurately consider all of the possible predictors. The first model considers all possible predictor variables excluding the ASVAB composite scores. The second model, which we discuss in section C, considers all possible predictor variables while excluding the ASVAB subscores.

1. Initial Variable Relationship Exploration

Figure 7 shows a series of plots that provide an initial look at the nature of the relationships between each independent variable and the time2E4. The red line in each plot is a regression trend line that describes the mean-relationship between the two variables.

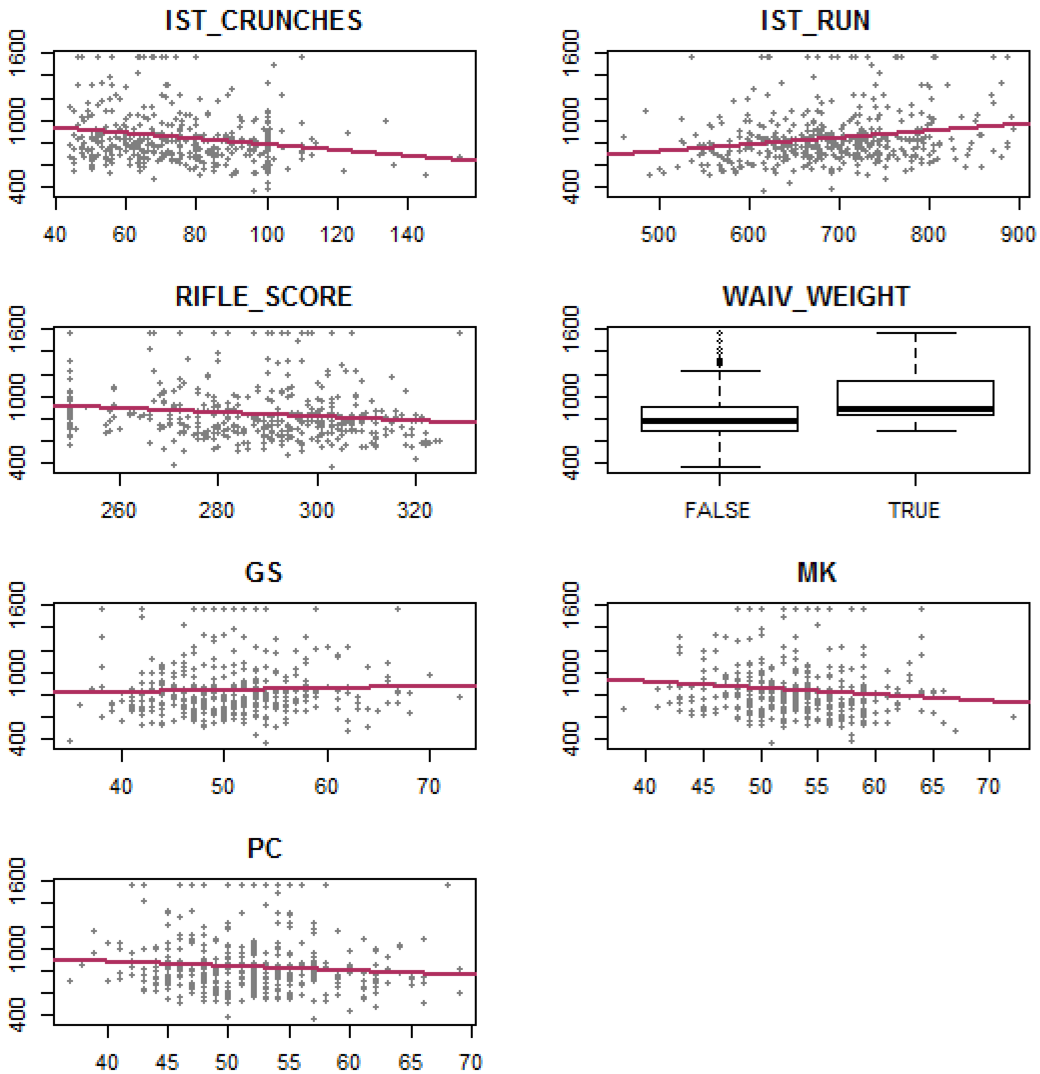

Figure 7. Initial variable relationships to time to promote to E-4 for the 2010 data set

Note: Time2E4 is on the vertical axis of each plot, and each independent variable is on the horizontal axis.

An initial observation of the relationships between time2E4 and the independent variables suggests a presence of possible relationships between variables. For example, the downward trend of the red regression line in the IST_CRUNCHES plot indicates that as the number of crunches increases, the time to achieve the pay grade of E-4 decreases. Similarly, as the IST_RUN time increases, the time to achieve E-4 increases.

2. Evaluation of the Regression Model

We explore the possibility that the response variable, time2E4, may need to be transformed in order to better satisfy the assumptions of a linear regression model. Based on the application of the Box-Cox procedure as described in Chapter III, the dependent variable, time2E4, is transformed by being raised to the power –0.7.

Prior to estimating the linear regression model, we conduct variable selection in order to find a near-optimal model based on the original set of independent variables. We begin with 22 possible predictor variables, as listed in Table 5, exluding the ASVAB composite scores. Variable selection using Best Subsets Regression with cross-validation is performed to find the best subset of the original independent variables as discussed in Chapter III. Figure 8 shows the results of fitting the linear regression model for an individual Marine's predicted time2E4.

```
lm(formula = Ytime ~ IST_CRUNCHES + IST_RUN + RIFLE_SCORE + WAIV_WEIGHT +
    +GS + MK + PC, data = Master10)

Residuals:
       Min         1Q     Median         3Q        Max
-0.0044329 -0.0008939  0.0000736  0.0010470  0.0062517

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)      4.348e-03  1.734e-03   2.507  0.01254 *
IST_CRUNCHES     1.177e-05  4.180e-06   2.816  0.00509 **
IST_RUN         -2.530e-06  9.829e-07  -2.574  0.01040 *
RIFLE_SCORE      1.260e-05  4.061e-06   3.103  0.00205 **
WAIV_WEIGHTTRUE -8.545e-04  4.021e-04  -2.125  0.03414 *
GS              -4.092e-05  1.383e-05  -2.958  0.00327 **
MK               4.516e-05  1.491e-05   3.030  0.00260 **
PC               3.780e-05  1.505e-05   2.513  0.01236 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.001551 on 413 degrees of freedom
Multiple R-squared:  0.1432, Adjusted R-squared:  0.1286
F-statistic: 9.859 on 7 and 413 DF,  p-value: 2.181e-11
```

Figure 8. All variables with ASVAB subscore model output

Based on the results from Figure 8, the variables included in the model are statistically significant with p-values of less than 0.05, as seen in the "Pr(>|t|)" column.

Table 7 shows the descriptive statistics for the six quantitative variables included in the model. The descriptive statistics shown are mean, median, standard deviation, minimum value, and maximum value.

Table 7. Descriptive statistics for the quantitative variables used in the analysis of time to achieve E-4 using ASVAB subscore and all predictors

Variable	**Mean**	**Median**	**Standard Deviation**	**Minimum**	**Maximum**
IST_CRUNCHES	75.41	73	19.51	44	155
IST_RUN	690.90	690	83.66	460	892
RIFLE_SCORE	287.50	290	19.42	250	329
GS	50.58	50	6.35	35	73
MK	53.00	53	5.14	38	72
PC	51.47	51	5.85	37	69

We explore the necessity for non-linear transformations of the independent variables using partial residual plots (Faraway, 2005). Shown in Figure 9, we use cubic basis splines with four interior knots in order to determine if a non-linear transformation of the predictor variables would improve the model. It is clear that straight lines can be fit within the confidence bands of each of these plots, which suggests that a simple linear model formulation should be adequate. We confirm this by conducting an F-test, with (42,370) degrees of freedom in order to compare the results from a model with variable transformation versus a model without transformation. The resulting F-statistic is 1.5163 with a p-value of 0.1715. This comparison indicates that the model with transformations is not significantly different than the model without transformation at the $\alpha = 0.05$ test level. Therefore, we do not reject the null hypothesis and conclude that non-linear transformation of the predictor variables is not necessary.

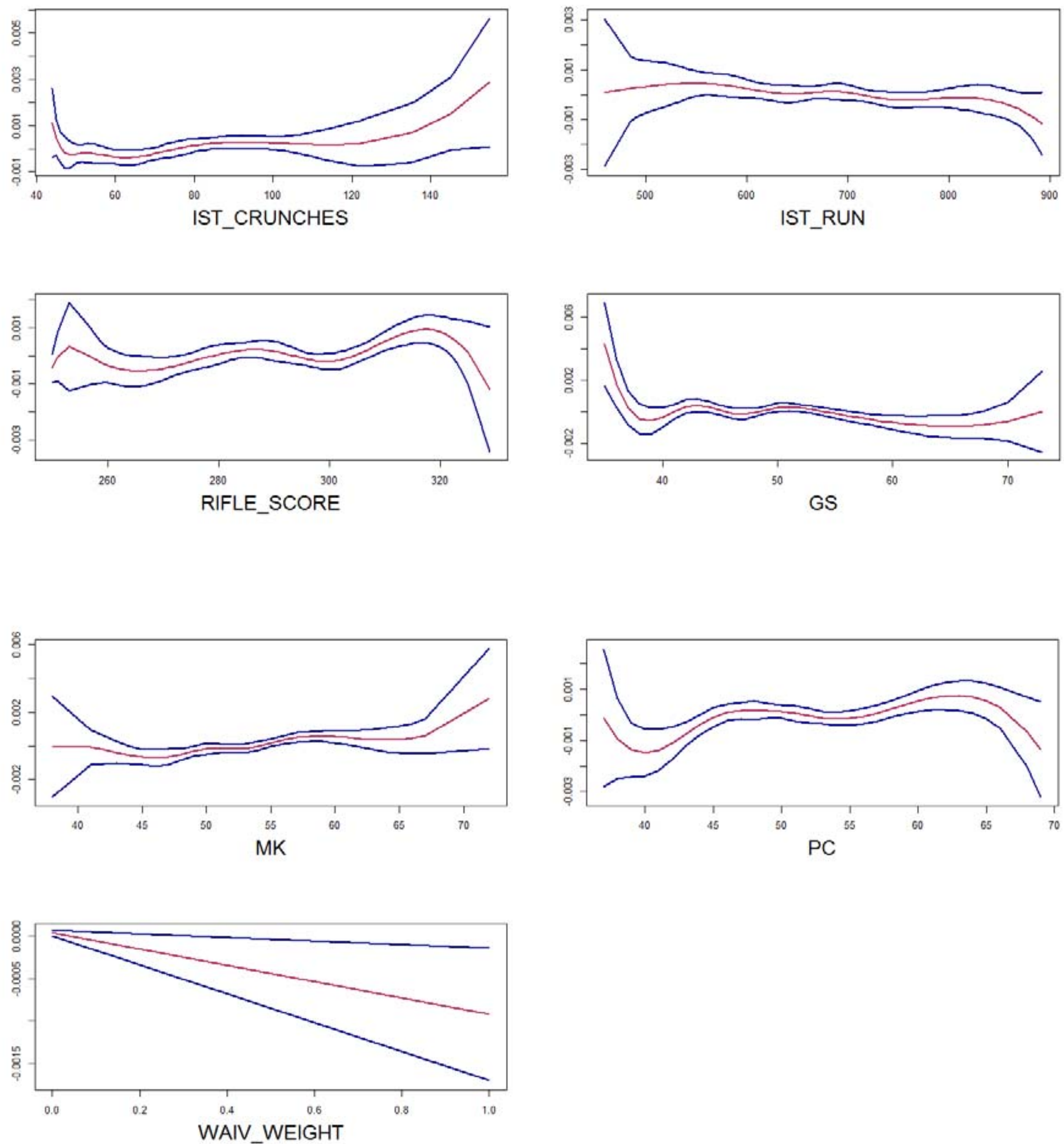

Figure 9. Partial residual plots of the predictor variables used in the analysis of time to achieve E-4 using ASVAB subscore and all predictors

Note: The red line is the cubic regression spline, and the blue lines are 95 percent confidence bands. If a straight line fits between the blue confidence bands, a good indication of a linear relationship exists.

The model diagnostic plots shown in Figure 10 indicate that the model assumptions are met and support the findings of the model.

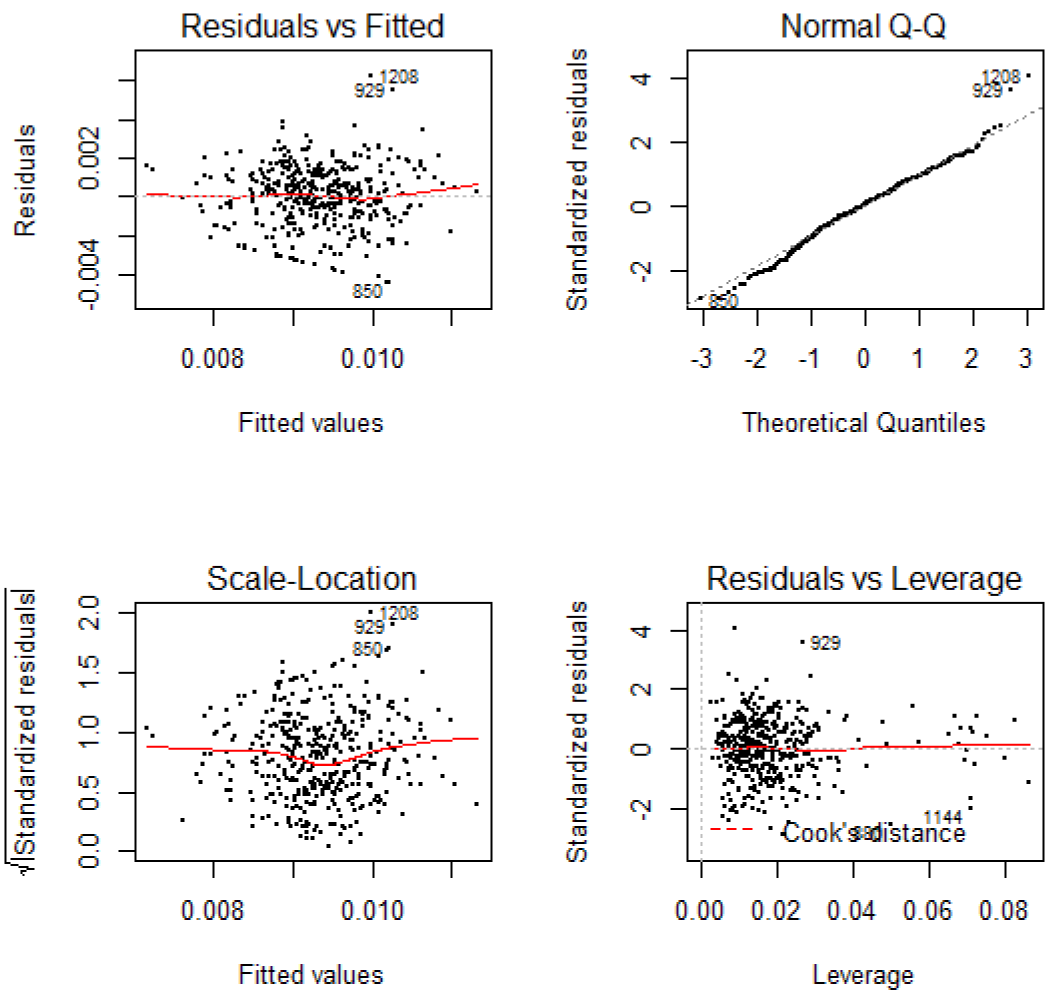

Figure 10. All variables with ASVAB subscores model diagnostics, after Box-Cox transformation

The Residuals vs. Fitted plot shows no signs of heteroscedasticity as there are no obvious patterns of unequal spread about the horizontal axis, thus indicating that the residuals exhibit constant variance. The Normal Q-Q plot indicates that the distribution of our data supports normality as the points trend nearly to a straight line. Finally, the Residuals vs. Leverage plot indicates that there are no overly influential data points in the model. The largest value for Cook's distance is 0.044, which is well below the commonly used warning value of 0.5. The plots in Figure 10 indicate that the model assumptions have been met and provide a valid model.

3. Explanation of the Model Results

From the model fit in Figure 8, we find that the most significant predictor variables for time2E4 are RIFLE_SCORE, MK, GS, IST_CRUNCHES, IST_RUN, PC, and WAIV_WEIGHT. It is important to note that while these variables are statistically significant in this model, they would not necessarily be statistically significant or have the same level of significance when modelled with a different year of records. The model results differ from those of the Computed Tier Score model and show different relationships between the entry-level attributes and each dependent variable. This provides evidence that the two metrics, or dependent variables, used in our analysis are substantially different.

To evaluate the effect each predictor variable has on the estimated time to achieve the pay grade of E-4, we use the median values shown in Table 7 to create a notional Marine for comparison. This notional Marine not receiving a weight waiver has an estimated time2E4 of approximation 787.2 days, with a 95 percent confidence interval of [526.6, 1380.3]. If the notional Marine received a weight waiver before entering service, then the estimated time2E4 is approximately 902.2 days, with a 95 percent confidence interval of [576.4 , 1739.3].

Tables 8 and 9 show the individual effect on the estimated time2E4 when increasing or decreasing the six numerical predictor variables individually by 10 percent; as well as varying WAIV_WEIGHT from false to true. Beginning in the second column, each column shows the effect on the predicted time2E4 by changing only the heading variable while holding all other variables constant. The “Difference” row shows the individual impact that each change in the predictor variable has on time2E4. The “Accounting for censoring” row shows the predicted time2E4 while accounting for censoring in the model, using the method described in Chapter IV for fitting regressions to censored data. The variable names have been shortened for presentation of the data.

Table 8. Effect of increasing predictor variable values on predicted time to achieve the pay grade of E-4

Variable	**Notional**	**CRUNCHES**	**RUN**	**RIFLE**	**GS**	**MK**	**PC**	**WEIGHT**
CRUNCHES	73	80	73	73	73	73	73	73
RUN	690	690	621	690	690	690	690	690
RIFLE	290	290	290	319	290	290	290	290
GS	50	50	50	50	55	50	50	50
MK	53	53	53	53	53	58	53	53
PC	51	51	51	51	51	51	56	51
WEIGHT	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
Time2E4	**787.2**	**777.5**	**766.8**	**745.5**	**812.4**	**761.0**	**765.1**	**902.2**
Difference	**-**	**-9.7**	**-20.4**	**-41.7**	**25.2**	**-26.2**	**-22.1**	**115.0**
Accounting for censoring	791.2	780.8	769.8	749.1	817.1	764.6	767.9	914.1

Note: The changes to each predictor variable are indicated by the red numbers, while holding all other values of the predictor variables constant.

Table 9. Effect of decreasing predictor variable values on predicted time to achieve the pay grade of E-4

Variable	**Notional**	**CRUNCHES**	**RUN**	**RIFLE**	**GS**	**MK**	**PC**	**WEIGHT**
CRUNCHES	73	66	73	73	73	73	73	73
RUN	690	690	759	690	690	690	690	690
RIFLE	290	290	290	261	290	290	290	290
GS	50	50	50	50	45	50	50	50
MK	53	53	53	53	53	48	53	53
PC	51	51	51	51	51	51	46	51
WEIGHT	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
Time2E4	**782.2**	**797.2**	**808.6**	**833.2**	**762.4**	**815.1**	**810.5**	**902.2**
Difference	**-**	**15.0**	**26.4**	**51.0**	**-19.8**	**32.9**	**28.3**	**120.0**
Accounting for censoring	791.2	802.0	813.7	837.6	766.7	819.5	815.8	914.1

Note: The changes to each predictor variable are indicated by the red numbers, while holding all other values of the predictor variables constant.

From Table 8, the largest improvement in predicted time2E4 results from an increase in Rifle Score, followed by MK, PC, Run Time, and Crunches, respectively. Receiving a weight waiver significantly impacts the predicted value in a negative way, by increasing the predicted time2E4 by 115 days. Table 9 presents the effects of decreasing each of the independent variables by the same magnitudes of change used in Table 8. As shown in the model summary presented in Figure 8, the GS ASVAB subscore indicates a surprisingly negative relationship with achieving the pay grade of E-4. This may be due to the correlation of the GS subscore to the other predictor variables present in the model, and warrants further investigation as additional data become available. The last row of these two tables gives the results of applying the survreg function in R to account for the twenty censored values of time2E4. Not surprisingly, the predicted times to promotion are somewhat larger when censoring is taken into account, although the effect is minimal.

C. ANALYSIS OF THE TIME TO ACHIEVE E-4 USING ALL POSSIBLE PREDICTOR VARIABLES INCLUDING ASVAB COMPOSITE SCORES

1. Evaluation of the Regression Model

We first explore the possibility of transforming the response variable, time2E4, using the application of the Box-Cox procedure outlined in Chapter III. Based on an application of this procedure, the dependent variable was transformed by being raised to the power –0.7,

We conduct variable selection in order to find a near-optimal model based on the original set of 20 independent variables, as listed in Table 5, exluding the ASVAB subscores scores. Best Subsets Regression with cross-validation is used to identify a subset of predictor variables for the development of the regression model. Figure 11 shows the results of fitting the linear regression model using the optimal set of independent variables for an indivual Marine’s predicted time to achieve the pay grade of E-4. There was no need for non-linear transformation of variables, as the predictive power of the model would not be improved.

```
lm(formula = Ytime ~ IST_CRUNCHES + IST_RUN + RIFLE_SCORE + WAIV_WEIGHT +
    CL_SCORE, data = Master10)

Residuals:
       Min         1Q     Median         3Q        Max
-0.0045221 -0.0008783  0.0001143  0.0010144  0.0062726

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)      5.198e-03  1.696e-03   3.065  0.00232 **
IST_CRUNCHES     1.262e-05  4.229e-06   2.983  0.00302 **
IST_RUN         -2.733e-06  9.956e-07  -2.745  0.00632 **
RIFLE_SCORE      1.050e-05  4.058e-06   2.588  0.01000 **
WAIV_WEIGHTTRUE -8.106e-04  4.071e-04  -1.991  0.04711 *
CL_SCORE         2.029e-05  8.727e-06   2.325  0.02056 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.001575 on 415 degrees of freedom
Multiple R-squared:  0.1123,	Adjusted R-squared:  0.1016
F-statistic:  10.5 on 5 and 415 DF,  p-value: 1.657e-09
```

Figure 11. All variables with ASVAB composite scores model output

The results of model fitting shown in Figure 11 indicate that the variables included in the model are statistically significant with p-values of less than 0.05.

The descriptive statistics for the four quantitative variables included in the model are displayed in Table 10, and include mean, median, standard deviation, minimum value, and maximum value.

Table 10. Descriptive statistics for the quantitative variables used in the analysis of time to achieve E-4 using ASVAB composite score and all predictors

Variable	**Mean**	**Median**	**Standard Deviation**	**Minimum**	**Maximum**
IST_CRUNCHES	75.41	73	19.51	44	155
IST_RUN	690.90	690	83.66	460	892
RIFLE_SCORE	287.50	290	19.42	250	329
CL_SCORE	103.40	101	8.87	87	137

The model diagnostic plots given in Figure 12 indicate that the model assumptions are met and support the findings of the model.

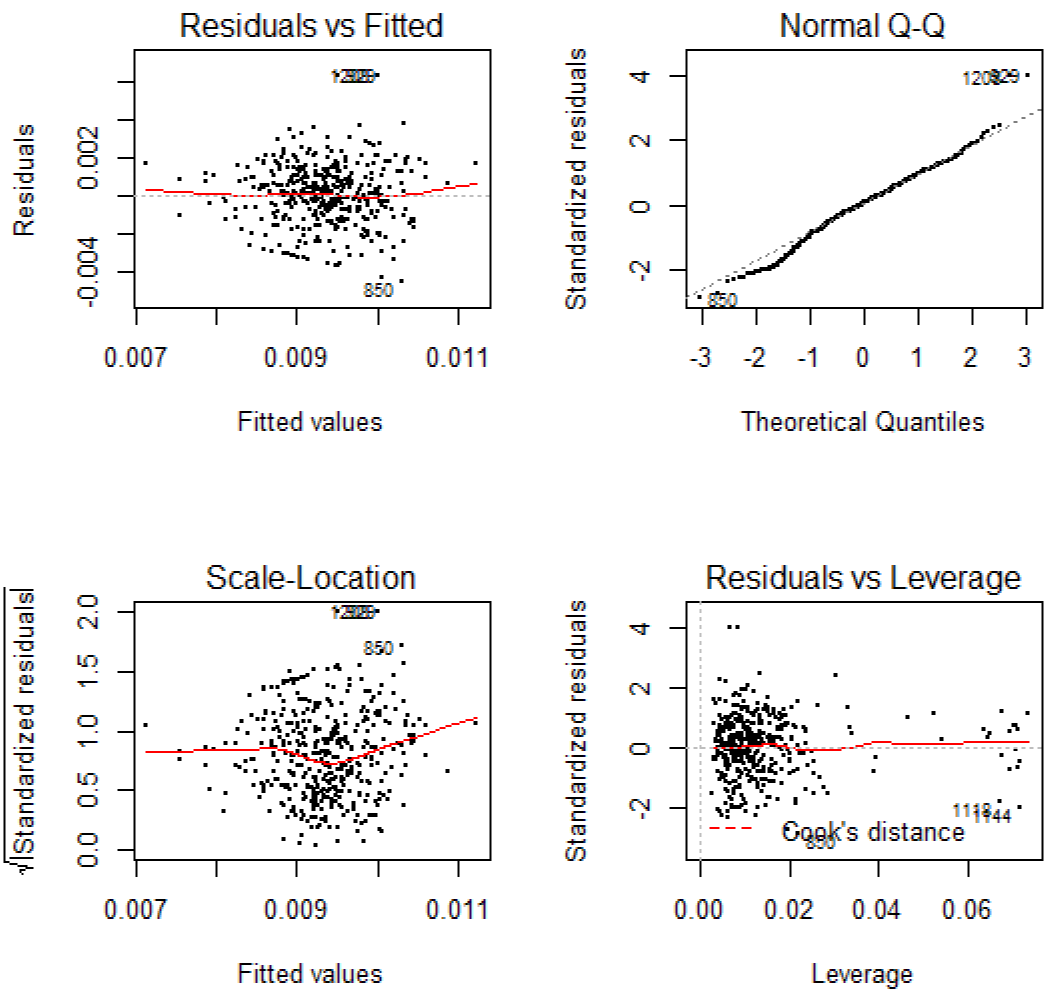

Figure 12. All variables with ASVAB composite scores model diagnostics, after Box-Cox transformation

The diagnostic plots provide evidence that the errors are independent, have constant variance, are normally distributed, and contain no overly influential observations that could effect the model.

2. Explanation of the Model Results

From the fitted model in Figure 11, we have determined that the most significant predictor variables are IST_RUN, IST_CRUNCHES, RIFLE_SCORE, CL_SCORE, and WAIV_WEIGHT. We evaluate the effect that each predictor variable has on the estimated time to achieve the pay grade of E-4 by using the median values shown in Table 10 to create a notional Marine for comparison. This notional Marine without a weight waiver has an estimated time2E4 of approximation 794.9 days, with a 95 percent confidence interval of [527.6, 1415.3]. If the notional Marine received a weight waiver before entering service, then the estimated time2E4 is approximately 905.1 days, with a 95 percent confidence interval of [574.3 , 1770.882].

Tables 11 and 12 show the individual effect on the estimated time2E4 when increasing or decreasing the six numerical predictor variables individually by 10 percent; as well as varying WAIV_WEIGHT from false to true. The changes to each predictor variable are indicated by the red numbers. Beginning in the second column, each column shows the effect on the predicted time2E4 (in days) by changing only the heading variable while holding all other variables constant. The "Difference" row shows the individual impact that each change in the predictor variable has on time2E4. The "Accounting for censoring" row shows the predicted time2E4 while accounting for censoring in the model, displaying only minimal effect from censoring. The variable names have been shortened for presentation of the data.

Table 11. Effect of increasing predictor variable value on the predicted time to achieve the pay grade of E-4

Variable	**Notional**	**CRUNCHES**	**RUN**	**RIFLE**	**CL_SCORE**	**WEIGHT**
CRUNCHES	73	80	73	73	73	73
RUN	690	690	621	690	690	690
RIFLE	290	290	290	319	290	290
CL_SCORE	101	101	101	101	111	101
WEIGHT	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
Time2E4	**794.9**	**784.2**	**772.5**	**759.2**	**770.8**	**905.1**
Difference	**-**	**-10.7**	**-22.4**	**-35.7**	**-24.1**	**110.2**
Accounting for censoring	798.9	787.5	775.4	763.0	774.3	917.0

Note: The changes to each predictor variable are indicated by the red numbers, while holding all other values of the predictor variables constant.

Table 12. Effect of decreasing predictor variable values on the predicted time to achieve the pay grade of E-4

Variable	**Notional**	**CRUNCHES**	**RUN**	**RIFLE**	**CL_SCORE**	**WEIGHT**
CRUNCHES	73	66	73	73	73	73
RUN	690	690	759	690	690	690
RIFLE	290	290	290	261	290	290
CL_SCORE	101	101	101	101	91	101
WEIGHT	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
Time2E4	**794.9**	**805.7**	**818.4**	**833.4**	**820.2**	**905.1**
Difference	**-**	**10.8**	**23.5**	**38.5**	**25.3**	**110.2**
Accounting for censoring	798.9	810.6	823.6	837.9	824.9	917.0

Note: The changes to each predictor variable are indicated by the red numbers, while holding all other values of the predictor variables constant.

From Table 11, the largest improvement in predicted time2E4 results from an increase in Rifle Score, followed by CL_SCORE, Run Time, and Crunches, respectively. Receiving a weight waiver significantly impacts the predicted value in a negative way, by increasing the predicted time2E4 by 117.9 days. Table 12 presents the effect of degrading each of the dependent variable and provides the same ranking relationship of the independent variables.

3. Evaluation and Comparison of the Regression Model Results for the ASVAB Subscore Model and the ASVAB Composite Score Model

This section provides a summary and comparison of the model outputs from the two models considered in predicting time2E4; the regression model that uses all possible predictor variables including the ASVAB subscores and the regression model that uses all possible predictor variables including the ASVAB composite scores.

Table 13 displays a summary of the model predictions for a notional Marine that did not receive a weight waiver.

Table 13. Comparison of model results for a notional Marine that did not receive a weight waiver

Model	Variables included in Model	Predicted time2E4 w/out Weight Waiver	95% CI
ASVAB Subscore	IST_CRUNCHES, IST_RUN, RIFLE_SCORE, GS, MK, PC, WAIV_WEIGHT	787.2	[526.6, 1380.3]
ASVAB Composite Score	IST_CRUNCHES, IST_RUN, RIFLE_SCORE, CL_SCORE, WAIV_WEIGHT	794.9	[527.6, 1415.3]

Table 13 displays similar model outputs. Both models find IST_CRUNCHES, IST_RUN, RIFLE_SCORE, and WEIGHT_WAIV to be statistically significant for inclusion. The relationship of each of these variables is the same in both models in terms of increasing or decreasing the predicted value of the dependent variable. Each model provides similar predictions and 95 percent confidence intervals for the predicted time2E4.

D. EXPLORATION OF COMBINING THE DATA INTO A MULTI-YEAR MODEL (FY2008–FY2010)

This section of the analysis explores the possibility of pooling the data from each year into one complete data set of Marines with the 0621 MOS from FY2008 through FY2010. Pooling the data into a multi-year study allows us to determine if the entry-level attributes are consistently predictive over time. The breakdown of the number of observations used by year is shown in Table 14. The total number of observations included in the model is 1,126.

Table 14. Summary of the number of observations used by year

Fiscal Year	Number of Observations
2008	351
2009	354
2010	421
Total	1,126

1. Evaluation of the Regression Model

We begin with 18 possible predictor variables, as listed in Table 5, exluding the ASVAB subscores. Based on an application of the Box-Cox procedure, the dependent variable, time2E4, was transformed by being raised to the power –0.3. In order to determine if the data from individual fiscal years can be pooled to fit a common model, we add the fiscal year as a categorical variable and run the regression model. The results of fitting the linear regression model are displayed in Figure 13.

```
lm(formula = (time2E4)^(-0.3) ~ year + Age + GENDER + WEIGHT +
    IST_CRUNCHES + IST_RUN + RIFLE_SCORE + WAIV_WEIGHT + CL_SCORE,
    data = Master, subset = tt.noSeps)

Residuals:
      Min        1Q    Median        3Q       Max
-0.030314 -0.007128  0.001173  0.007072  0.042389

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)      1.294e-01  7.020e-03  18.426  < 2e-16 ***
year09          -5.718e-03  1.108e-03  -5.159 2.94e-07 ***
year10          -7.218e-03  1.107e-03  -6.518 1.08e-10 ***
Age              6.490e-04  1.870e-04   3.470 0.000540 ***
GENDERM         -2.713e-03  1.374e-03  -1.975 0.048554 *
WEIGHT          -3.628e-05  1.457e-05  -2.490 0.012910 *
IST_CRUNCHES     4.975e-05  2.117e-05   2.350 0.018953 *
IST_RUN         -2.462e-05  5.229e-06  -4.708 2.82e-06 ***
RIFLE_SCORE      5.167e-05  1.286e-05   4.017 6.30e-05 ***
WAIV_WEIGHTTRUE -3.741e-03  1.453e-03  -2.575 0.010155 *
CL_SCORE         5.879e-05  1.717e-05   3.424 0.000639 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01165 on 1115 degrees of freedom
Multiple R-squared:  0.09637, Adjusted R-squared:  0.08826
F-statistic: 11.89 on 10 and 1115 DF,  p-value: < 2.2e-16
```

Figure 13. Multi-year model including year variable

The model shown in Figure 13 included the individual fiscal years as being significant predictors in the regression. This reveals that the year variable provides statistically significant information in predicting a Marine’s time to achieve the pay grade of E-4. The regression coefficients for year09 and year10 have significant effects on the dependent variable. This result argues against pooling the data from different years to fit a common model.

The descriptive statistics for the six quantitative variables included in the model are displayed in Table 15.

Table 15. Descriptive statistics for the quantitative variables used in multi-year model

Variable	**Mean**	**Median**	**Standard Deviation**	**Minimum**	**Maximum**
Age	20.13	19.62	1.87	17.28	30.03
WEIGHT	163.10	161.00	27.64	96	259
IST_CRUNCHES	70.00	67.00	18.32	39	155
IST_RUN	706.60	717.00	79.62	450	918
RIFLE_SCORE	270.3	282.0	20.28	248	332
CL_SCORE	99.07	101.00	21.52	85	140

Further support for not pooling the data from different years to fit a common model can be found by inspecting side-by-side boxplots of the residuals from the regression broken down by year, as shown in Figure 14.

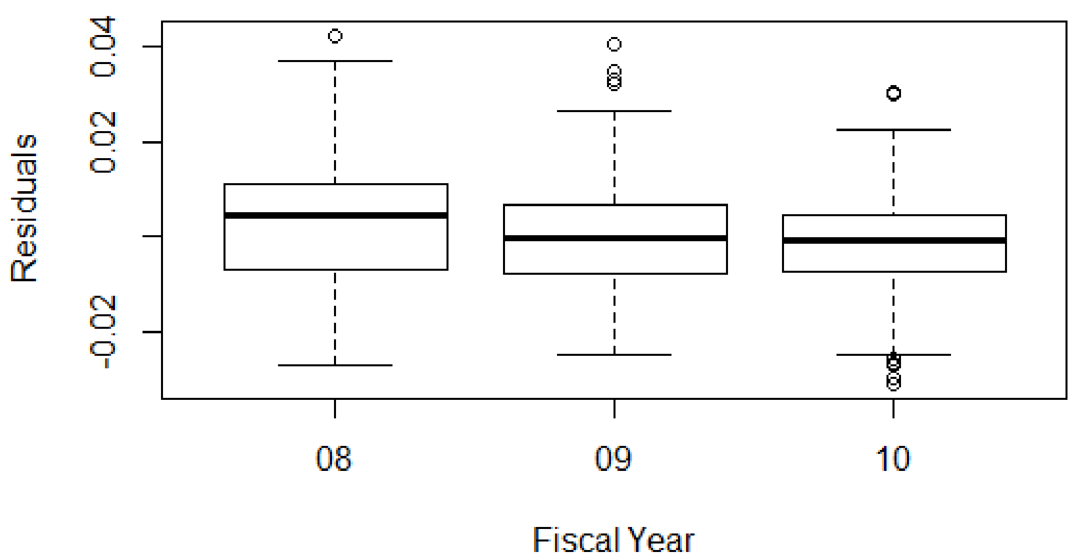

Figure 14. Comparison of regression errors across three years of data using boxplots with time2E4 as the outcome variable

As seen in the comparison of the boxplots, the variance of the regression errors decreases from 2008 to 2009, and then again from 2009 to 2010. The regression errors do not exhibit constant variance and violate the basic model assumptions. This decrease in the variance of the regression errors possibly indicates that the accuracy of the data improves across the years, and could be explained simply by the changing Marine Corps policies from year to year for Marine recruitment or changing promotion requirements. We conclude that the individual data sets or possibly the relationships are not homogeneous across years. Most importantly, this exercise suggests that this analysis should be repeated on an annual basis, and not pooled into a multi-year study, at least into the near future.

E. CHAPTER SUMMARY

This chapter provides a detailed explanation of the four models created in order to study the relationships between entry-level attributes of Marine recruits with the 0621 MOS and two dependent variables; the Computed Tier Score and time2E4. Statistically significant relationships between both dependent variables and the entry-level attributes are found to exist.

V. CONCLUSIONS AND RECOMMENDATIONS

A. CONCLUSIONS

This thesis develops multivariate linear regression models to identify the most important determinants of a Marine's advancement to the pay grade of E-4 within the 0621 Field Radio Operator MOS. Further, we determine that these models have statistically significant predictive power for a Marine's Computed Tier Score at the time of eligibility for re-enlistment. We present evidence that these studies should be repeated on an annual basis vice pooling the data into multi-year studies. Specifically, four questions are considered in our analysis, which are presented in this section with our findings.

1. Do significant relationships exist between entry-level attributes of a USMC recruit and the USMC Computed Tier Score or the time for a Marine to achieve the pay grade of E-4?

This study has determined that there are statistically significant relationships between the entry-level attributes of a Marine recruit and the USMC Computed Tier Score, as well as the time to achieve the pay grade of E-4 within the 0621 MOS in the USMC. Entry-level attributes of Marine recruits can be utilized to predict these dependent variables.

2. What are the most influential independent variables that predict the Computed Tier Score and the rate of promotion to E-4 in the 0621 MOS?

The most influential independent predictor variables that allow prediction of the Computed Tier Score are found to be IST_RUN, WAIV_WEIGHT, IST_CRUNCHES, GT_SCORE, and WEIGHT. The predicted value of Computed Tier Score increases as IST_RUN and WEIGHT decrease, or as IST_CRUNCHES and GT_SCORE increase. Of particular interest, CL_SCORE and MM_SCORE exhibit a decreasing relationship with the Computed Tier Score. The latter does not imply that doing well on these scores should be a negative factor in evaluating a Marine, but it does suggest that relationships between the predictor variables may lead to a statistical result of this kind.

As shown in Table 13 (Chapter IV), IST_CRUNCHES, IST_RUN, RIFLE_SCORE, GS, MK, PC, WAIV_WEIGHT, and CL_SCORE are the most influential predictor variables used to determine success as defined in terms of the time to achieve the pay grade of E-4. RIFLE_SCORE is the most influential predictor variable that has a beneficial relationship to time2E4, while receiving a weight waiver prior to entering service has the largest negative effect. RUN_TIME, MK, PC, and CL_SCORE follow RIFLE_SCORE as providing positive impact on the predicted time2E4, all having a similarly influential effect.

3. What insight does this analysis provide in terms of recommending changes to the current entrance criteria for the 0621 Field Radio Operator MOS?

While IST_CRUNCHES, IST_RUN, RIFLE_SCORE, and WEIGHT provide insight into the predicted time2E4, the relationships of time2E4 with GS, MK, PC, and CL_SCORE merit further exploration for inclusion in the entrance criteria of a Field Radio Operator. Interestingly, EL_SCORE, which is currently used as one of the criteria for entry into the 0621 MOS, was not found to have a statistically significant relationship to time2E4. This does not indicate that EL_SCORE is not a significant measure of suitability to the 0621 MOS, but rather that other ASVAB scores may provide similar information in predicting time2E4.

4. What direction should a future study take to examine ways in which the matching of USMC recruits to MOS fields can be improved?

In order to explore other suitability to MOS measures that could lend to predicting a successful match, there is a need for the development of new suitability measures. As explained in Chapter II, the Center for Naval Analyses (CNA) developed job performance measures for a limited number of MOSs in order to test proficiency in performing duties as outlined by the USMC. We recommend that similar job performance measures be created across all high-density MOSs in order to support studies focused on matching a USMC recruit to his or her MOS. This study can then be replicated using a metric that is focused on the quality of matching as the dependent variable for analysis.

B. RECOMMENDATIONS FOR FUTURE WORK

Based on the findings in this study, the following future work is suggested to expand this field of research and the scope of our findings.

The models and methodologies utilized in this study should be expanded to other high-density MOSs within the USMC. With a better understanding of the influential predictors within each MOS, further recommendations can be made to other MOSs considered. Further, an optimization of the placement of a selected pool of Marines into the MOSs that need to be filled would provide the USMC with a tool to improve the quality of matching available Marines to the MOSs.

The USMC Manpower Database, TFDW, is a vast resource of data that can be used to support future studies. Data collection through the USMC database requires an extensive level of knowledge of the system and is not user-friendly. The improvement and development of a user-friendly and readily accessible database would be a significant advantage to those using TFDW for data analysis purposes. More specifically, the development of a complete and more detailed data dictionary and user interface would improve the availability of data.

Further exploration and development of new performance and suitability measures could provide useful results when analyzing the influence of various predictor variables. With the development of standardized performance metrics, this study could then be expanded and provide further insight into the job matching problem.

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF REFERENCES

ASVAB fact sheet. (n.d.). Retrieved from Official Site of the Armed Services Vocational Aptitude Battery: http://official-asvab.com/docs/asvab_fact_sheet.pdf

ASVAB scoring. (n.d.). Retrieved from Official Site of the Armed Services Vocational Aptitude Battery: http://official-asvab.com/understand_res.htm

Carey, N. B. (1993). *The Marine Corps Job Performance Measurement (JPM) project: A bibliography.* Alexandria, VA: Center for Naval Analysis.

Faraway, J. J. (2005). *Linear models with R.* Boca Raton, FL: Chapman & Hall/CRC.

History of miltary testing. (n.d). Retrieved from Official Site of the Armed Services Vocational Aptitude Battery: http://official-asvab.com/history_res.htm

Mayberry, P. W. (1990). *Validation of ASVAB against infantry job performance.* Alexandria, Va: Center for Naval Analysis.

R Development Core Team. (2014). R: A language and environment for statistical computing. Retrieved from http://www.R-project.org

Rautio, L. J. (2011). *Study of standards used to screen recruits for assignment to the communicatioons field in the U.S. Maine Corps.* Master's thesis, Naval Postgraduate School, Monterey, CA.

USMC. (2009). *Marine Corps Order 1230.5B, Classification Testing.*

USMC. (2013). *Marine Corps Order 1200.17E, Military Occupational Specialty Manual (Short Title: MOS Manual).*

THIS PAGE INTENTIONALLY LEFT BLANK

INITIAL DISTRIBUTION LIST

1. Defense Technical Information Center
   Ft. Belvoir, Virginia

2. Dudley Knox Library
   Naval Postgraduate School
   Monterey, California